Perceptually Training Viewers against Misleading Data Visualizations with Informative feedback

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Abstract

Misleading visualizations are increasingly prevalent, with a surge in their negative impact on data interpretation, often leading to misunderstandings and poor decision-making. To address this issue, we investigate the impact of informative feedback within perceptual training targeting misleading visualizations. Our results show that informative feedback significantly enhances viewers' perceptual skills, improving both accuracy and efficiency in interpreting misleading data visualizations. Additionally, participants demonstrated a transfer effect, applying their developed perceptual skills to novel misleading visualizations beyond those encountered during training. These findings highlight the potential of perceptual training with informative feedback to strengthen viewers' resistance to misleading data visualizations, offering valuable insights for educational practices aimed at fostering viewers' resistance to misleading data visualizations.

Keywords: Misinformation; Misleading data visualization; Perceptual learning; Informative feedback

Introduction

The rise of misleading visualizations has become a pressing concern in today's society, reflecting the escalating battle against misinformation. (Bliss & Patino, 2020). These misleading visualizations, a powerful form of misinformation, can distort data interpretation, leading to flawed perceptions and poor decision-making (Cui et al., 2023; Lisnic et al., 2023; Lo et al., 2022). For instance, as shown in Figure 1, when the y-axis of a bar chart begins at a value greater than zero (e.g., 34% in this case), it visually exaggerates differences between data points. While the actual numerical difference between the two bars is only 4.6 percentage points, the truncated y-axis creates the illusion of a far more dramatic change. Such distortions can mislead viewers into perceiving trends that the data does not substantiate, fueling misinformation and confusion (Cui et al., 2024; Kerns & Wilmer, 2021). To address this, interventions are needed to enhance viewers' skills in detecting and resisting misleading visualizations.

Graph comprehension involves both perceptual and conceptual processing (Cleveland & McGill, 1984; Curcio, 1987; Kosslyn, 1989; Rau, 2017). Perceptual processing is a bottom-up, automatic process that happens quickly and is often unconscious. This allows viewers to form an initial mental representation based on basic visual features (e.g., color, length, position) (Cui & Liu, 2021). By contrast, conceptual processing is a top-down, effortful process that requires considerable cognitive capacity and willful engagement with the graph. While interventions often target conceptual processing (Camba et al., 2022; Raschke & Steinbart, 2008) inexperienced viewers rely more on perceptual processing, increasing their susceptibility to misleading visuals (Trickett & Trafton, 2006). Therefore, this study investigates perceptual training as a method to address misleading data visualizations.

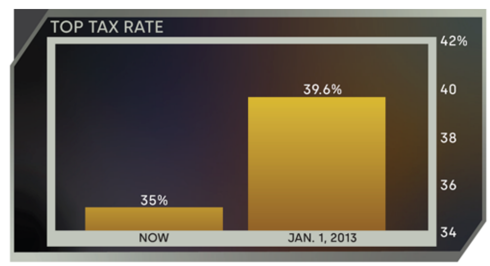

Figure 1: The example of a bar chart shows how a truncated y-axis can mislead viewers.

Perceptual training, an instructional approach that trains viewers to efficiently extract information from graphs (Kellman & Massey, 2013), can improve the ability to detect patterns (Cui et al., 2018; Matthews et al., 2024). However, applying the conventional format of perceptual training to misleading data visualization can have limitations as they mostly focus on *correct* visualizations that convey domain-relevant information (Kellman et al., 2010; Rau & Wu, 2018). By contrast, interventions for misleading data visualizations often must incorporate deceptive or *erroneous* examples to demonstrate misleading practices (Camba et al., 2022; Ramly et al., 2021; Yang et al., 2021). This likely requires more informative feedback to support the complex cognitive processes involved in accurate interpretation. Thus, this paper examines the role of feedback in perceptual training for misleading data visualizations.

Related Works

Perceptual training presents participants with many varied examples in the context of meaningful domain-relevant tasks that require efficient information extraction (Kellman & Massey, 2013; Rau, 2017). Based on immediate feedback, viewers inductively learn to attend to and efficiently extract relevant information (Koedinger et al., 2012; Rau, 2017). Conventional perceptual training typically presents numerous *correct* examples, allowing viewers to inductively

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learn to attend to and recognize meaningful visual patterns (Kellman et al., 2010; Kellman & Garrigan, 2009). Building on research showing that detailed explanation can disrupt inductive processing during perceptual training (Schooler et al., 1997; Shanks, 2005), conventional perceptual training typically provides simple, nonverbal feedback, such as color highlighting to indicate whether the learner's response is correct or incorrect (Kellman et al., 2010; Rau & Wu, 2018).

In the context of data visualization, perceptual training can enhance a viewer's ability to quickly recognize potentially misleading elements and to adjust their interpretation of the data accordingly. However, compared to conventional perceptual training, when dealing with misleading data visualizations, training likely must target an additional cognitive step. When identifying a misleading element in the given misleading visualization, viewers need to simultaneously generate its non-misleading counterpart from which to extract accurate information. In such a situation, providing only simple and nonverbal feedback might be insufficient. Viewers might need additional guidance to identify the misleading elements and imagine a corresponding visualization in which this element is corrected.

Prior research leads to conflicting predictions as to the effectiveness of informative feedback in perceptual training. On the one hand, informative feedback seems to contradict the principles of designing perceptual training. As mentioned, detailed explanations have been shown to interfere with inductive processing during learning (Schooler et al., 1997; Shanks, 2005). Although prior research has demonstrated the effectiveness of perceptual training that provides simple feedback (Kellman et al., 2010; Rau & Wu, 2018), it has not systematically compared simple one to informative feedback.

On the one hand, extensive research on feedback demonstrates the advantages of informative feedback that provides additional information rather than merely indicating the correctness of viewers' responses to the tasks, especially for challenging and complex tasks (Moreno, 2004; Narciss & Huth, 2004; van der Kleij et al., 2012). Consequently, informative feedback can help viewers more quickly attend to key visual features, thereby reducing the cognitive load required to process misleading visualizations. Especially because perceptual training with misleading visualizations is more complex, a reduction of cognitive load might be effective. Nevertheless, this notion has not been tested in the context of perceptual training that targets inductive rather than analytical cognitive processes.

Informative feedback about misleading visualizations can be given either in the form of text or as a visual annotation. Textual feedback can describe where and how misleading elements appear in a given visualization. While providing detailed explanations has proven effective at increasing resistance to misinformation in other contexts (Chan et al., 2017; Van Der Meer & Jin, 2020), their effectiveness has not been examined for misleading data visualizations, let alone in the context of perceptual training. Therefore, in this study, we constructed textual feedback that explains the presence and nature of misleading elements in various visualizations. The advantage of text-based informative feedback is that viewers have to reference back and forth between the visualization and the feedback text, thereby becoming cognitively active at discovering a misleading element based on guidance. Such learner activity has proven effective in

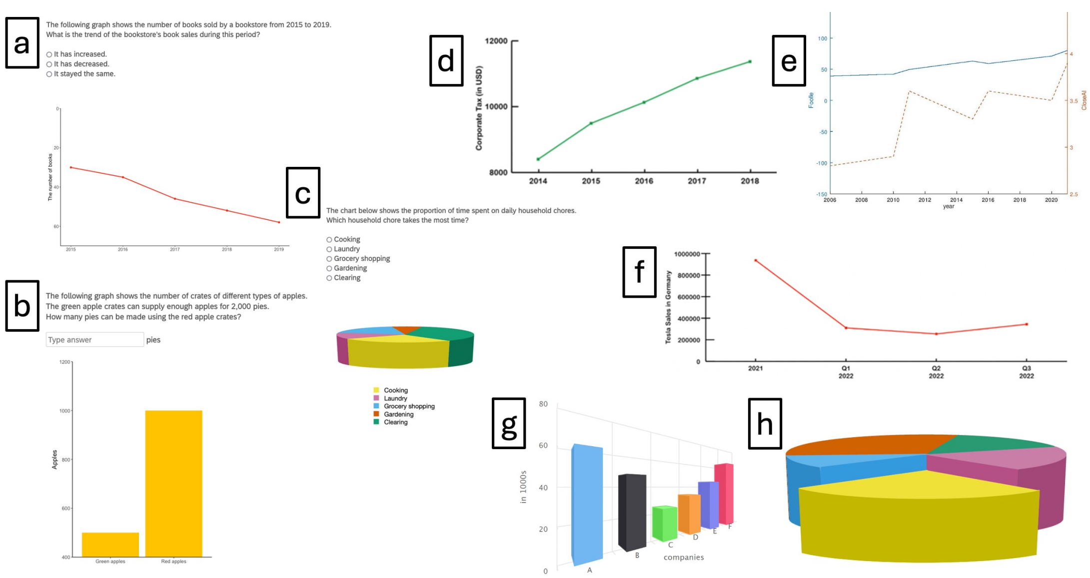

Figure 2: Examples of estimation tasks three misleading data visualization types that covered in perceptual training (a, b, c) and types that were not covered in training (d, e, f, g, h): (a) estimation task for a line chart with an inverted y-axis, asking to estimate the trend of the line, (b) a task for a bar chart with a truncated y-axis, asking to estimate certain values based on two bars' data points, and (c) a task for a pie chart with a 3D effect, asking to find a largest slice, (d) line chart with truncated y-axis, (e) line chart with dual axes, (f) line chart with manipulated x-axis, (g) bar chart with 3D effect, and (h) pie chart with pop-out and 3D effect.

instructional settings that involve visualizations (Bodemer et al., 2004). Visual feedback, on the other hand, can directly highlight where misleading elements appear in a given visualization. In our study, visual feedback uses visual cues to point out specific misleading elements. This approach directly directs participants' visual attention to misleading elements, which has proven effective in other types of perceptual training (Jarodzka et al., 2013).

To our knowledge, no prior research has systematically examined the role and impact of feedback in perceptual training for misleading visualizations, especially the role of informative feedback. Therefore, this study compares the effects of various types of informative and simple feedback on training viewers' perceptual training. Furthermore, we explore transfer effects to misleading data visualizations that viewers did not previously encounter during the perceptual training. Altogether, we addressed three research questions (RQ) in this study:

RQ1. Does feedback in perceptual training enhance viewers' perceptual processing for misleading data visualizations?

RQ2. Is informative feedback effective at training viewers' perceptual processing for misleading data visualizations?

RQ3. Do the effects of perceptual training transfer to novel types of misleading data visualizations?

Method

Participants

We recruited a total of 252 participants (65% were female, 29% were male, and the rest preferred not to disclose) from our university, in the Midwestern U.S. Participants aged 23.26 on average. They accessed all study materials online using Qualtrics.

Perceptual Training Intervention

The training incorporated three types of misleading data visualizations, including line charts with inverted y-axes, pie charts with 3D effects, and bar charts with truncated y-axe, sequenced randomly. We selected these visualization types (1) because they are prevalent, and (2) because our prior research (Rho et al., 2024) showed that they are highly deceptive.

For each visualization type, viewers completed simple information extraction tasks, similar to a task that one might face when being presented with a data graph on a news media post on social media. When presented with line charts (Figure 2a), viewers were asked to evaluate trends as increasing, decreasing, or stable. For bar charts (Figure 2b), they had to estimate or compare values between two bars. For pie charts (Figure 2c), they had to identify the largest segment. Following Ramly and colleagues' (2021) findings on optimal example quantity in perceptual training for misleading data visualizations, we developed 15 varied examples for each visualization type, resulting in a total of 45 examples (3 types × 15 examples) for the training. The number of examples was fixed, rather than training to a mastery criterion, to standardize the training experience across participants and isolate the effect of feedback type. All tasks were designed to be completed within 30 seconds, with immediate feedback provided for each response.

Experimental design

Participants were randomly assigned to one of four experimental conditions, each receiving different types of feedback for their extraction tasks: control, simple feedback (Figure 3a), text-based informative feedback (Figure 3b), or visual-based informative feedback (Figure 3c). In the control condition, participants received no feedback. The simple feedback condition corresponds to conventional perceptual training, which provides minimal information, notifying participants of their answer's (in-)correctness and indicating that the given visualization was misleading. The text-based informative feedback condition received an indication of their answer's (in-)correctness, a detailed explanation of how the non-misleading visualization is manipulated by applying misleading elements to misinform, and the correct answer in text form. Finally, the visual-based informative feedback condition received an indication of their answer's (in-) correctness, visual cues highlighting the misleading elements in the original visualization using red boxes, and a corrected non-misleading version of the same visualization.

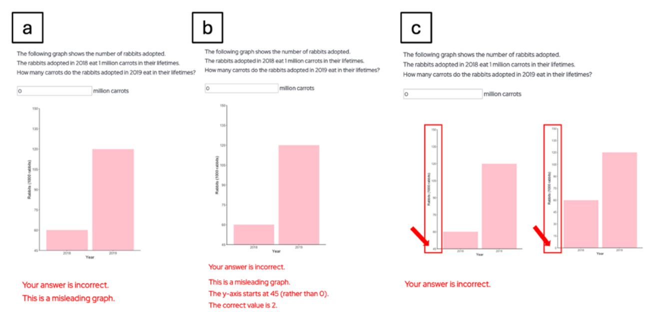

Figure 3: examples of (a) simple feedback, (b) text-based informative feedback, and (c) visual-based informative feedback.

Measurements

We employed a pretest and posttest to assess participants' effectiveness of perceptual training. The tests were designed to evaluate both direct learning outcomes on the same visualization types participants encountered during the training and transfer effects to novel misleading visualization types that participants did not encounter during the training. Besides the three visualization types that were used in the training (i.e., inverted line charts, 3D pie charts, and truncated bar charts), five additional types were included in the pretest and posttest to assess the transfer of learning. These included line charts with dual axes, line charts with manipulated x-axes, bar charts with 3D effects, pie charts with pop-out effects, and line charts with truncated y-axes (see Figure 2). These transfer visualizations were chosen to examine both near transfer (to visually similar graphs) and far transfer (to visually dissimilar graphs). The pretest and posttest each contained 32 items, consisting of four pairs of visualizations for each of the eight types. Within each pair, both visualizations represented the same data, but one contained misleading elements (i.e., misleading data visualizations) while the other did not (i.e., non-misleading data visualizations). Test items presented individual visualizations with questions requiring participants to extract quantitative information. Two equivalent but distinct versions of the test were developed to reduce item familiarity effects. Participants were randomly assigned to receive different versions across the pretest and posttest to counterbalance item exposure, ensuring that while the questions tested the same concepts, the specific visualizations were different. Calculator use was prohibited during testing.

To assess improved perceptual skills for misleading data visualizations, we used two metrics: accuracy and efficiency. Accuracy scores were calculated as the percentage of correctly answered items on each test. Efficiency scores were computed using the normalized test scores for performance and the normalized time spent on the test for mental effort (Van Gog & Paas, 2008): efficiency score = $(z_{\text{score on test}} - z_{\text{time on test}}) / \sqrt{2}$. Efficiency scores take into account both accuracy and speed. While performance on non-misleading data visualizations served as a baseline, scores for misleading visualizations were the primary measure of interest.

Procedure

After informed consent, participants watched an instructional video that informed them that they would see a series of visualizations and answer questions about the information presented in the given visualization. The video also emphasized the need for participants to quickly extract information from the visualizations. After watching the video, participants completed three sessions, with a one-minute break between sessions. During the first session, participants took the pretest. In the second session, participants worked through the perceptual training according to their assigned condition. This training session lasted approximately 20 minutes on average. In the third session, participants took the post-test and took a short survey to provide demographic information (e.g., gender and age).

Results

We excluded participants from the analysis who missed answering any test items or who dropped the experiment. As a result, a total of 248 participants were included in the data set (control: n = 63, simple feedback: n = 61, text-based informative feedback: n = 62, visual-based informative feedback: n = 63). We report effect sizes using partial η^2 (p. η^2). An effect size between 0.01 to 0.05 corresponds to a small, between .06 and .13 corresponds to a medium, and larger than .14 corresponds to a large effect (Cohen, 1992). Table 1 provides averages and standard deviations for test scores and duration for misleading visualization types covered during training, while Table 2 provides similar information for visualization types not covered during training.

Table 1: Each condition's average test scores and duration for misleading data visualization types covered during training, values in parentheses are standard deviations.

	Test score		Duration (min)	
	Pre	Post	Pre	Post
Control	0.510	0.710	2.46	1.46
(no feedback)	(0.262)	(0.235)	(0.48)	(0.32)
Simple	0.483	0.825	3.00	2.02
feedback	(0.212)	(0.172)	(0.51)	(0.40)
Text-based	0.427	0.838	2.42	1.43
feedback	(0.204)	(0.163)	(0.42)	(0.32)
Visual-based	0.461	0.846	3.10	2.04
feedback	(0.243)	(0.180)	(1.02)	(0.40)

Table 2: Each condition's average test scores and duration for misleading data visualization types not covered during training, values in parentheses are standard deviations.

	Test score		Duration (min)	
	Pre	Post	Pre	Post
Control	0.561	0.546	5.03	4.33
(no feedback)	(0.141)	(0.165)	(1.17)	(1.18)
Simple	0.548	0.551	5.15	5.05
feedback	(0.136)	(0.146)	(1.24)	(1.12)
Text-based	0.529	0.574	5.44	4.18
feedback	(0.129)	(0.155)	(1.32)	(1.16)
Visual-based	0.533	0.561	5.41	5.06
feedback	(0.143)	(0.159)	(1.45)	(1.11)

Effects on misleading visualizations encountered during training

To examine the effectiveness of overall feedback in perceptual training (RQ1) and informative feedback (RQ2), we conducted an adjusted Kruskal-Wallis test using regression residualization. We chose this approach because the posttest distributions were not normally distributed (ps < .005). To adjust for covariates, we first performed a linear regression analysis with posttest scores for visualizations participants encountered during training as the dependent variable and the corresponding pretest scores as the covariate. Residuals from this regression model were then used as the dependent variable in the Kruskal-Wallis test, with the condition as the independent factor. Post-hoc comparisons were conducted using Dunn's test with Holm correction for multiple comparisons.

Regarding accuracy scores, there was a significant medium-sized difference between conditions at posttest, $H(3)= 32.378$, $p < .001$, p. $\eta^2 = .119$ (Figure 4). Compared to the control condition (i.e., no feedback), participants were significantly more accurate in the simple feedback condition, $p(adj) < .001$, and the text-based informative feedback condition, $p(adj) < .001$, and the visual-based informative feedback condition, $p(adj) < .001$. There was no significant difference in accuracy among feedback conditions (ps > .1).

Regarding efficiency scores, there was also a significant medium-sized difference between conditions at posttest, $H(3) = 30.299$, $p < .001$, p. $\eta^2 = 0.111$. Compared to the control condition (i.e., no feedback), participants were significantly more efficient in the simple feedback condition, $p(adj) = .007$, and the text-based informative feedback condition, $p(adj) < .001$, and the visual-based informative feedback condition, $p(adj) < .001$. Additionally, compared to the simple feedback condition, participants were marginally more efficient in the textual-based informative feedback condition, $p(adj) = .052$. No other post hoc comparisons were significant.

Transfer effects on misleading visualizations not encountered during training

To test for transfer effects, we applied the same adjusted Kruskal-Wallis test using regression residualization with test scores related to visualizations that participants did not encounter during training. Regarding accuracy scores, there was a marginally significant small difference between conditions at posttest, $H(3) = 2.650$, $p = .049$, p. $\eta^2 = .018$. Specifically, these effects were driven by pie charts with 3D and pop-out effects, for which we found a medium-sized difference between conditions, $H(3) = 23.016$, $p < .001$, p. $\eta^2 = .081$. Compared to the control condition, participants were significantly more accurate in the simple feedback condition, $p(adj) = .005$, the text-based informative feedback condition, $p(adj) < .001$, and the visual-based informative feedback condition, $p(adj) < .001$. We found no transfer effects for other novel visualization types. There were no differences between conditions on efficiency scores.

Discussion

This study examined the effects of feedback in perceptual training aimed to enhance viewers' perceptual skills for misleading data visualizations (RQ1). Further, we investigated whether informative feedback is effective for perceptual training addressing misleading data visualizations (RQ2). We found that the feedback conditions significantly outperformed the no-feedback control condition on both accuracy and efficiency measures. Moreover, results showed that informative feedback resulted in slightly higher efficiency gains, meaning that viewers were faster at extracting correct information from misleading visualizations, likely reflecting less mental effort. Notably, simple feedback yielded no significant advantage in efficiency over the control condition. The observed improvements in efficiency suggest that participants not only became more accurate but also faster at processing misleading visualizations. This can indicate a refinement of perceptual skills, enabling them to extract information more quickly. For example, participants improved their ability to discern differences in bar heights in truncated bar charts and to identify distortions of trend in line charts, demonstrating enhanced perceptual sensitivity.

Additionally, this study found the possible transfer effects to novel types of misleading data visualizations that viewers did not encounter during the training (RQ3), specifically 3D pie charts with pop-out effects.

These findings extend prior research on perceptual training in several ways. First, our findings demonstrate the effectiveness of informative feedback in training perceptual skills for misleading data visualizations. Given that prior research has not systematically contrasted the effect of simple and informative feedback in perceptual training, this is, to our knowledge, the first study to show that informative feedback can enhance viewers' perceptual skills.

Whereas instructional design principles for conventional perceptual training suggest using simple feedback so as not to disrupt inductive processing, our results suggest that this approach may have limitations in the context of misleading data visualizations. Although simple feedback was effective at enhancing accuracy, it led to lower gains in terms of efficiency. This finding indicates that informative feedback reduces the mental effort of viewers when faced with misleading data visualizations. Given that misinformation is rampant in contexts where there are many demands on our attentional resources (e.g., social media), this is a noteworthy finding. Informative feedback, whether text-based or visual-based, provided detailed information about the location of misleading elements and demonstrated how non-misleading

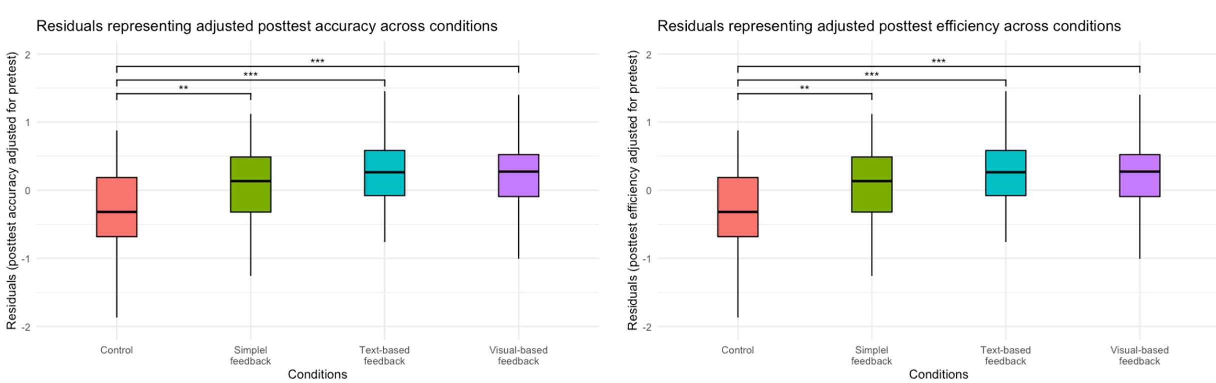

Figure 4: Residuals representing adjusted posttest accuracy scores (left) and efficiency scores (right) across conditions. Error bars depict standard errors. $^{**}p < .01$, $^{***}p < .001$

versions would appear. This likely enabled the viewer to notice misleading elements and to mentally adjust their interpretation of the shown data.

Our study does not necessarily indicate that informative feedback always enhances the effectiveness of perceptual training more so than simple feedback. As mentioned, most perceptual training focuses on correct visualizations. Perceptual training for misleading visualizations involves more complex processes, as detailed above, which might account for the effectiveness of informative feedback in the present study. Nevertheless, we note that prior research on perceptual training has not systematically contrasted simple and informative feedback. We hope that our findings inspire new research to more closely examine the role of feedback in training perceptual skills.

Interestingly, we found no difference between text-based informative feedback and visual-based informative feedback when it comes to misleading visualizations encountered in the training. This is surprising because they seem to target different aspects of the perceptual training. Textual feedback provides explicit information that requires cross-referencing with the visualization. By contrast, visual feedback provides visual cues that are integrated with the visualizations and involves comparisons between the misleading and correct visualizations. Both versions hence actively involve viewers in discovering which aspects of the misleading visualization account for its misinformative impact. Overall, it does not seem to make a difference which means feedback prompts viewers to actively engage with the misleading nature of visualizations, as long as they are. It would be interesting to examine possible combinations of text-based and visual-based feedback to leverage the strengths of each version of feedback to actively engage viewers.

Finally, we found that the effect of our perceptual training with feedback transferred to a subset of novel misleading data visualization types not included in the training. Considering that viewers received the perceptual training for a line chart with an inverted y-axis, a bar chart with a truncated y-axis, and a pie chart with 3D effects, the transfer effect occurred only for one misleading data visualization type that shared similar visual elements, a pie chart with 3D and pop-out effect. The observed transfer effect being limited to this type of visualization may be explained by a near transfer effect. Near transfer occurs between tasks that share a high surface similarity – incidental features that are not conceptually relevant (Barnett & Ceci, 2002). In this case, the novel misleading data visualizations, such as pie charts with 3D and pop-out effects, demonstrated a near transfer effect, likely due to their more apparent surface commonalities with the misleading data visualizations used in the perceptual training (i.e., pie charts with 3D effects). These similarities may have facilitated the near transfer. Furthermore, the feedback provided during perceptual training emphasized these visually common features, potentially scaffolding viewers to recognize them more effectively. Thus, the informative feedback may have offered the optimal level of scaffolding, which became evident through the observed near-transfer effect.

Limitations and Future Research

Our findings should be considered in light of several limitations. First, our participants were limited to undergraduate students. Future research should examine the generalizability of these findings to more diverse and broader populations, including professionals, older adults, and individuals with varying levels of visual literacy. Second, while our study focused on a limited but popular set of misleading data visualization types, the range of visualizations implemented in the real world is much more diverse. To increase the applicability of perceptual training interventions, future studies should explore a wider variety of misleading visualization types. Third, this study compared the effects of training across different types of visualizations (bar charts, line charts, and pie charts). However, these visualization types involve different perceptual and cognitive processes, making direct comparisons challenging (Cui & Liu, 2021). While we attempted to control for difficulty within each visualization type, it is possible that inherent differences in the tasks influenced our results. Future research could investigate the differential effects of perceptual training on specific visualization types, carefully controlling for task difficulty and perceptual demands. Lastly, while we interpreted improvements in efficiency as evidence of enhanced perceptual skills, it is important to acknowledge that our study design does not entirely disentangle perceptual processing from conceptual understanding. Future research could employ methods such as eye-tracking to directly measure perceptual processes.

Conclusion

In today's data-driven society, it is all the more important that we develop interventions that can make viewers resilient to misleading data visualizations. Our findings show that feedback is necessary for viewers to train their perceptual skills allow them to spot misleading elements in visualizations. We found that feedback was more effective when it was informative. Additionally, we found that an advantage of informative feedback was transferred to a novel type of misleading data visualizations that perceptual training did not cover. Thereby, our findings extend research on perceptual training by highlighting that informative feedback may be more effective in some contexts. Additionally, our findings show that existing interventions for misinformation, which mostly focus on conceptual understanding of visual misinformation, could be augmented by perceptual training. This seems important given that misinformation generally occurs in contexts where cognitive resources are stretched thin (e.g., on social media). As misleading visualizations continue to proliferate across digital platforms, such interventions will likely provide a valuable approach for equipping viewers with the competencies needed to navigate and critically evaluate data representations in everyday contexts.

Acknowledgment

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