Measuring the Persuasive Effects of Narrative Visualizations

Matthew Chambers
Clemson University
chambe5@clemson.edu

Bryan Denham
Clemson University
bdenham@clemson.edu

Abstract—Narrative visualizations utilize visualization rhetoric techniques to convey an intended story. Designers use these techniques to engage viewers, communicate insights, or persuade viewers toward an encoded message. Due to the rise of data journalism, many narrative visualizations are consumed by large audiences. A challenge for designers and researchers lies in understanding how audiences respond to persuasive messages communicated using a narrative visualization. To address this issue, we study how people's attitudes change toward (or away from) a message experienced through three treatments: a table, a data visualization, and a narrative visualization. Using a repeated measures design, we investigate the persuasive effects of these presentation types across the demographics of a representative sample. Unlike prior studies, we find that the different presentation types alone do not significantly affect attitude change with a polarizing topic. However, we find that the interaction between presentation type and education level do significantly affect attitude change. Further analysis of the persuasive outcomes revealed that narrative visualizations are more persuasive amongst those with higher levels of education, while data visualizations are more persuasive amongst those with lower levels of education. The study's results are useful to practitioners and researchers as the findings reveal how different visualizations influence attitude change across demographics.

Index Terms - Narrative visualization, persuasive visualization, visualization rhetoric.

Introduction

In an era of data-driven communication, visualizations have become a critical tool for communicating with large audiences. During the COVID-19 pandemic, organizations like the CDC relied heavily on data visualizations to communicate public health information [1]. While these data visualizations were largely informative, news organizations including the *New York Post* and *Washington Post* use narrative visualizations to tell stories [2]. Narrative visualizations rely on the use of persuasive, rhetorical techniques to convey an intended story to viewers [3]. While data visualizations are typically used to provide supporting evidence, narrative visualizations integrate a narrative into the visualization itself [2]. As narrative visualization continues to gain popularity as a tool for communicating with large audiences, it is critical to understand how these visualizations impact and influence people.

Rettberg [4] refers to visualization as "a form of communication that emphasizes data" (p.45). Viewing visualization as a means of communicating allows us to see its subjective nature. While there is a perception that visualizations are objective [4], data does not have an inherent visual form [5]. A designer must choose how to represent the data visually and how the intended message will be encoded. These decisions about chart selection and graphic attributes, such as the use of color and size, build "rhetorical force" in narrative visualizations [5]. Narrative visualizations can then be seen as an emerging form of rhetoric as they can be used to persuade and drive change. Since these rhetorical techniques can lead to effects on the viewer's interpretation of a message, additional research is needed to understand their persuasive impact.

Hullman and Diakopoulos first introduced the concept of visualization rhetoric as a framework for understanding how design choices encode meaning into narrative visualizations and how viewers decode those messages. Visualization rhetoric serves to "constrain what is salient to the user given human visual perception tendencies" (p.2237). Hullman and Diakopoulos [3] explicated the rhetorical techniques utilized in narrative visualizations to provide a tool that helps researchers and designers understand how narrative visualizations communicate. While this framework is useful for understanding how to design narrative visualizations, there is a lack of research around how narrative visualizations persuade; particularly compared to other presentations such as tables or data visualizations. To study these effects, the visualization rhetoric framework [3] was used to inform the design of the narrative visualization created for this study.

2158-1002/25/$31.00 ©2025 IEEE
DOI 10.1109/ProComm64814.2025.00063

Prior research studies [6], [7] attempted to measure the difference in the persuasive effect of presenting a table and a data visualization. However, these studies did not explore how narrative visualizations affect persuasive outcomes. Additionally, these studies did not investigate the effects of demographic factors such as age or education level, which is key to understanding how large audiences are influenced by different presentations of data [8].

To address these gaps in the current body of research, we designed a study to test how narrative visualizations influence people's attitudes towards a polarizing topic. Our research builds on visualization rhetoric, narrative visualization, and persuasive visualization research to investigate the persuasive effects of data tables, data visualizations, and narrative visualizations across demographics. In our study, we measure persuasive effect as the change in a viewer's attitude [6]. This study used a repeated measures design to assess the attitudes of participants before and after being randomly presented with either a data table, data visualization, or narrative visualization. The results of this study are useful to practitioners and researchers as the findings reveal how narrative visualizations impact attitudes across demographics.

Related Work

In this section, we give an overview of the reviewed literature. First, we provide an overview of the visualization rhetoric framework to define the available rhetorical devices in narrative visualizations and how they can be applied. Then, we explore the differences in a data visualization and a narrative visualization for the purpose of defining these terms as the treatments used in our study. We also explore prior research studies in persuasive visualization, which inform the methods in this study. Finally, we explore the demographic variables *age* and *education level* regarding their effects on data literacy and thus the inclusion of these variables in the study.

I. *Visualization rhetoric framework*

In the emerging field of visualization rhetoric, current research addresses the rhetorical design choices that can be applied to narrative visualizations. Hullman and Diakopoulos [3] define *rhetoric* as "to be associated with persuasion as a result of the implicit motivation of the speaker to gain other adherents to a preconceived view or conclusion" (p. 2232). Further, they define visualization rhetoric as "the set of processes by which intended meanings are represented in the visualization via a designer's choices and then shaped by individual end-user characteristics" (p. 2232). Specifically, Hullman and Diakopoulos describe the visualization rhetoric framework as a vocabulary of rhetorical devices that enable the communication of layered meanings. Subtle variations in applying these rhetorical devices can significantly affect the viewer's interpretation of a message [3]. Hullman and Diakopoulos defined four essential rhetorical techniques: *information access rhetoric, provenance rhetoric, mapping rhetoric, and procedural rhetoric*.

Information access rhetoric. A designer's first decision is choosing which data to display or omit. At the data layer, the designer makes choices about the data source selection, inclusion or exclusion of columns, and inclusion or exclusion of rows. Additionally, the designer may remove outliers or aggregate certain data elements.

Provenance rhetoric. In the age of disinformation and misinformation, citing sources is more important than ever. Providing a data source for a visualization helps to create trust through transparency. Provenance rhetoric strategies such as citing or linking data sources allow the viewer to validate visualizations and explore any data omission that may have occurred.

Mapping rhetoric. Mapping rhetoric is the process by which a visualization designer encodes information visually [3]. The designer maps data elements to the visual domain at the visual representation layer by selecting a chart type and then applying *pre-attentive attributes,* which can be used to direct attention [9]. Since human vision is selective to the pre-attentive attributes of size [10], length [11], color [11], and orientation [12], we can utilize these attributes to gain different interpretations and understanding from data [13].

Procedural rhetoric. Bogost [14] defines procedural rhetoric as "a practice of using processes persuasively" (p. 3). Procedural rhetoric utilizes anchoring techniques to convey and deliver a message [3]. The visualization layout is primarily driven by spatial ordering decisions such as where to place the title, narrative, and visualization. For example, if the audience primarily reads left to right, the title and narrative should appear at the top left.

II. *Narrative visualization*

Data visualizations have previously been used to enhance storytelling by providing supporting evidence that is usually referenced in a larger body of text [2]. However, narrative visualizations differ in that they integrate a narrative into the visualization itself [2]. Hullman and Diakopoulos [3] describe the rhetorical effect of narrative visualization as causing specific interpretations to become more likely; the viewer can then be guided towards a persuasive message. Segel and Heer [2] detail the use of annotated charts that utilize text to provide observations and explanations about the visualization. This concept is referred to as *messaging* and takes the form of headlines, captions, labels, or annotations [2] Horn [15] refers to this concept as *tight coupling*. Tight coupling is the link between the text and the visual that creates the message's meaning [15]. If either the text or the visual is deleted, the meaning of the message would be lost. This allows narrative-visualizations to serve as a stand-alone presentation rather than requiring a supporting written narrative. Segel & Heer [2] note that messaging is the most critical component when storytelling or communication is the primary goal. The researchers also illustrate the use of highlighting to direct attention and create more salient information [2].

III. Persuasive visualization

Prior research studies primarily focused on measuring the persuasive effects of text or tables and data visualizations. Tal and Wansink [7] demonstrated that the presence of a chart or graph increases persuasion. Half of the participants were treated with a text description, while the other half were treated with a graph. After the treatment, the participants were asked to rate the product's effectiveness. The results showed that those given the graph rated the effectiveness much higher than those given the text description.

Pandey et al. [6] utilized a different approach where a table was compared against a data visualization to determine potential persuasive effects. Echoing the work of Fogg [16], persuasion in this study was defined as "change in attitude" [6]. This research method was centered around determining if a data visualization would have a more persuasive effect than a data table when using the same data. Pandey et al. tested their hypothesis by designing an experiment to measure attitude change. First, participants were given a brief topic description. Participants were then given a pre-treatment attitude assessment before being exposed to a persuasive message. Then, the participants were randomly presented with either a data table or a data visualization. Participants were asked an attention check question to ensure they could interpret the data table or data visualization. After viewing one of the two randomly assigned treatments, participants were given a post-treatment attitude assessment. The difference in the pre-treatment and post-treatment attitudes was measured to quantify attitude change. The results of the experiment confirmed that data visualizations are more persuasive than data tables.

While Pandey et al. [6] recommended against using polarizing topics, Heyer et al. [17] chose to follow the study of Pandey et al. while evaluating potential persuasive effects in polarizing topics. This study compared the persuasive effect of interaction technique and medium. In this study, persuasion was defined as change in attitude. The interaction techniques either asked the participants to predict portions of the data or presented the participant with relevant data. The medium determined if the participant received a text description or a visualization. Both the text and the visualization treatments contained identical arguments. The study showed that the interaction technique was not significant as "participants were no more likely to change their attitude when asked to predict the data before-hand, than if they had simply viewed the data" (p.10). However, the visualizations were more persuasive than textual representations, even when using polarizing topics.

IV. Demographic measures

As narrative visualizations can be used to reach large audiences, it is important to understand how differences in audience demographics may impact persuasive outcomes. Prior research studies [6], [7], [17] all collected demographic data but did not investigate the interaction effects of these variables. However, a replication of Tal and Wansink's study concluded that follow-up studies should investigate the impact of demographics such as education level [18]. Additionally, a prior study showed that there was a disparity in the ability to comprehend visualizations between first-year students and those with bachelor's degrees or above [19]. Kennedy et al. [8] also recommended that visualization research adopt approaches widely used in communication studies where demographics such as age are investigated. As the use of narrative visualization continues to grow, it is essential to understand how visualizations are perceived by different age groups. In the United States, shifting population dynamics will result in the number of people over 65 doubling by 2050 [20]. Despite the perceived benefits of visualizing data, older adults tend to encounter difficulties interpreting more nuanced visualizations [21]. The current body of literature suggests that additional research is needed to understand how education level and age impact persuasive effects in more complex narrative visualizations.

METHOD

I. Participants

Data was collected by administering a voluntary survey to 600 participants recruited online through Prolific [22]. All participants were 18 or older, based in the United States, and the participants were selected to be representative of the United States population by age, sex, and ethnicity [23]. Before the survey was administered, approval for exempt status was obtained from the Institutional Review Board (IRB) at Clemson University.

II. Research instrument

Topic selection. The survey instrument was created by following the studies of Pandey et al. [6] and Heyer et al. [17]. While the study by Pandey et al. recommends against the selection of polarizing topics, Heyer et al. suggested that visualizations are more persuasive than tables, even if the issue is polarizing. As narrative visualization continues to gain adoption by designers and researchers, it becomes critical to understand how the medium influences viewer's perceptions when the topic is controversial. Therefore, the topic of gun violence was selected from ProCon.org, a website that provides a list of sourced pros and cons related to publicly debated issues [6].

This instrument specifically focused on assessing participants attitudes about gun suicides in the United States. From 1999 to 2019, gun deaths in the United States continued to increase [24]. Media coverage of gun deaths during this period generally centered around mass shootings and homicides [25]. However, gun suicides are not typically covered in the media, even though these numbers contribute to the rise in gun death rates. Jashinsky et al. [25] reported that "63% of gun US gun violence deaths occur from suicides while a little over 10% of the news stories discussed suicide" (p. 4). The goal of selecting this topic is to spotlight the impact of gun suicides in the United States, where media coverage is disproportionally focused on mass shootings and homicides [25].

Instrument design. The instrument contained 12 items in total. Items 1-3 measured the pre-treatment attitude toward gun suicides, with each utilizing a 7-point Likert scale. The three items asked participants to express their level of agreement or disagreement with the following statements: *1. In the United States, there should be greater public awareness of gun suicides. 2. In the United States, more funding should be allocated to gun suicide prevention. 3. In the United States, stronger gun laws would likely reduce suicide rates.* The responses ranged from Strongly Disagree (1) to Strongly Agree (7), which composed a 21-point index across the three items. The index ranged from a minimum of 3 to a maximum of 21. Item 4 served as an attention check question to ensure that the viewer was engaged and able to understand the presented data. Items 5-7 measured the post-treatment attitude toward gun suicides and asked participants to express their level of agreement or disagreement with the statements above. The responses ranged from Strongly Disagree (1) to Strongly Agree (7), which composed a 21-point index across the three items. The index ranged from a minimum of 3 to a maximum of 21. Questions 8-12 included five items used to collect demographic information.

Reliability. To ensure reliability for the pre-treatment attitude toward gun suicides and post-treatment attitude toward gun suicides indexes, Cronbach's α was used to measure internal consistency. First, Cronbach's α was computed for the three-item pre-treatment attitude toward gun suicides index ($\alpha = .788$) and was found to exceed the .70 recommended for high reliability [26]. Next, Cronbach's α was computed for the three-item post-treatment attitude toward gun suicides index ($\alpha = .836$), again exceeding the .70 recommended for high reliability [26]. With reliability of measurement confirmed in the study, the attitude toward gun suicides index measured before and after treatment was used as the dependent variable.

III. Research design and variables

The research design was informed by the studies of Pandey et al. [6], Tal and Wansink [7], and Heyer et al. [17], which assessed potential differences in attitudes after receiving a textual (table) or graphical (chart) treatment. The study followed an experimental design utilizing a randomly assigned treatment serving as a between-subjects factor used to study the effect on the dependent variable attitude toward gun suicides measured before and after treatment [27]. A mixed design was employed as both within-subjects and between-subjects factors were used in the study [27]. Since the attitude is evaluated using time (before/after), a repeated measures design was implemented [28]. A repeated measures design has the advantage of using the same participants before and after treatment, so researchers can generally assume that differences in the dependent variable are attributable to the experiment [28]. Error is reduced substantially as the variability in the within-subjects factor can be explained by the between-subjects factors [27]. A mixed repeated measures design also allows for the use of pair-wise comparison to evaluate the means of between-subjects factors [27].

IV. Treatment design

To test the persuasive effects of narrative visualizations, we also developed a table and a data visualization. The goal for designing the treatments was to spotlight the increase in gun suicides relative to gun homicides in the United States from 1999 to 2019. The data were retrieved for all suicide and homicide deaths caused by firearms between 1999 and 2019 using the CDC WISQARS database [24].

Data table. Information access rhetoric decisions (including or removing variables, categorizing, or aggregating data elements) at the data layer shape the communication at the visual representation and textual annotation layers [3]. For this analysis, the crude rates were used as these variables help to correct for population growth, so the total deaths and population were removed from the data set. Card et al. [29] refer to this process as data transformation. After the data transformation was complete, the data were displayed in a table (Figure 1).

Data visualization. Since the data show change over time, a line chart was chosen to display the data in a visual domain creating a data visualization. Visualizing the gun suicide rate and gun homicide rate together over time in a line chart helps to frame the message since the viewer can see the relative difference between the two variables [3]. The viewer is easily able to see the increase in the gun suicide rate relative to the gun homicide rate. In this data visualization, color was used to represent each variable categorically (Figure 2).

Narrative visualization. The narrative visualization (Figure 3) built upon the data visualization by integrating a narrative conveying the increase in gun suicides over time. To convey our message, we applied pre-attentive attributes to create more salient information and attract attention [30]. To accomplish this, we utilized mapping rhetoric techniques [3] where we applied the pre-attentive attribute

Gun Death Rate per 100,000 U.S. Residents 1999-2019

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Suicides per 100,000 people	6.0	5.9	5.9	6.0	5.8	5.7	5.8	5.7	5.8	6.0	6.1	6.3	6.4	6.6	6.7	6.7	6.9	7.1	7.3	7.5	7.3
Homicides per 100,000 people	3.9	3.8	4.0	4.1	4.1	4.0	4.2	4.3	4.2	4.0	3.8	3.6	3.6	3.7	3.6	3.5	4.1	4.5	4.5	4.3	4.4

FIGURE 1. DATA TABLE TREATMENT

of size to the gun suicides line to cause it to stand out. Then, color was added to focus the viewer's attention on the gun suicides line. The color "red" was used as it could create an association with death in Western audiences [31]. A source was added at the bottom to foster trust through transparency as a provenance rhetoric appeal [3]. Finally, text elements were added to integrate the message into the narrative visualization. The title and narrative were placed in the top left to accommodate the expectations of Western audiences [3]. Fonts can convey personas [32], so the title was designed to evoke a tone of seriousness. The color in the chart matches the color in the narrative. This creates tight coupling between the chart and the written narrative and contributes to the meaning in the message [15].

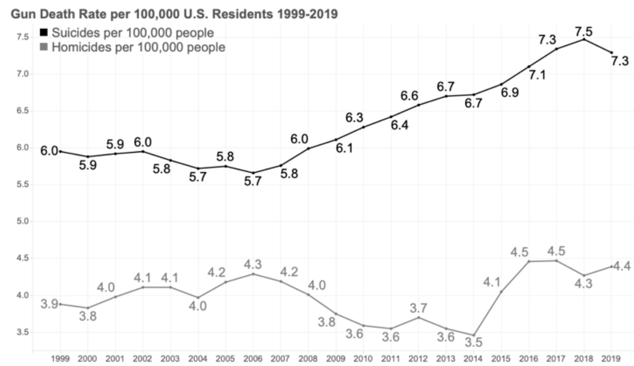

FIGURE 2. DATA VISUALIZATION TREATMENT

V. Procedure

Participants were recruited using Prolific and provided a link to the survey, which was deployed using Qualtrics. The study was anonymous, and no identifiable information was stored. Participants were provided information about the study, contact information, payment details, and were asked to provide consent before beginning the survey. After participants agreed to participate, they completed the pre-treatment attitude assessment. Participants were then randomly assigned one of three treatments: a data table, a data visualization, or narrative visualization. Participants were asked to view the treatment and answer an attention check question to ensure that the viewer understood how to interpret the treatment. Participants that answered the attention check question incorrectly were removed from the study and replaced. After viewing the treatment and answering the attention check question, participants completed the post-treatment attitude assessment. Finally, participants were asked to provide demographic information such as education level and age range.

VI. Statistical analyses

The data were extracted from Qualtrics and imported into SPSS for analysis. To analyze the interaction with the demographic variables, a four-way repeated measures mixed ANOVA was used with time representing two levels (before/after treatment) of a within-subjects factor, treatment, education level, and age range as the between-subjects factors, and the dependent variable was the

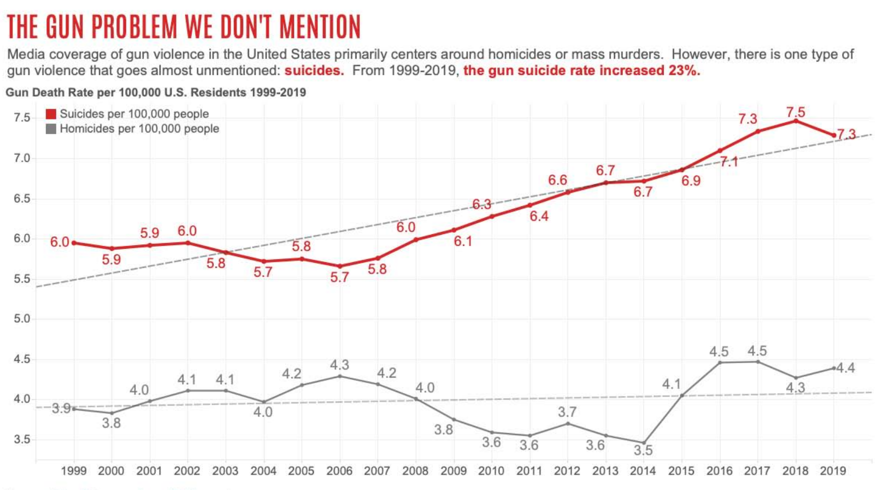

FIGURE 3. NARRATIVE VISUALIZATION TREATMENT

attitude toward gun suicides measured at the two times [27]. The assumption of sphericity was met due to the within-subjects factor only representing two levels [33]. For the repeated measures mixed ANOVA, Bonferroni pair-wise comparison was performed to evaluate the means for significant between-subjects factors [27]. The significance level used in the study was $p \leq .05$.

RESULTS

I. Participants

600 participants were recruited for the study, and participants were randomly assigned a treatment: 202 (33.7%) viewed a data table, 199 (33.2%) viewed a data visualization, and 199 (33.2%) viewed a narrative visualization. Of the 600 participants, 292 (48.7%) were male, 297 (49.5%) were female, and 11 (1.8%) were non-binary or preferred not to say/self-describe. 248 (41.3%) had an education level of associate degree and below while 352 (58.7%) had an education level of bachelor's degree or above. Demographics for age range are presented in Table 1.

TABLE 1. FREQUENCIES AND PERCENTAGES OF AGE RANGE STUDY PARTICIPANTS.

Age range	Frequency	Percent
18-24	82	13.7
25-34	115	19.2
35-44	98	16.3
45-54	92	15.3
55-64	129	21.5
65+	84	14.0
Total	600	100

II. Change in attitude

Study results. We first confirmed that the study influenced participants attitudes toward gun suicides in the United States. A one-way repeated measures ANOVA determined that there was a significant main effect for time, [F (1, 599) = 34.8, $p < .001$] The analysis indicated that the difference in the means of the pre-treatment attitude toward gun suicides index (M = 15.50, SD = 4.19, N = 600) and post-treatment attitude toward gun suicides index (M = 15.90, SD = 4.38, N = 600) was statistically significant. The study showed a medium effect (ηp^2 = .055) on persuasion [34].

Treatments. To understand the difference in attitude change between the treatments, a two-way repeated measures mixed ANOVA was performed. The main effect for time was significant, but the interaction effect between time and treatment was not significant. While the interaction plot (Figure 4) illustrates that all three treatments resulted in an increase in the mean attitude toward gun suicides index, the plot supports the finding that there was no significant variation between treatments.

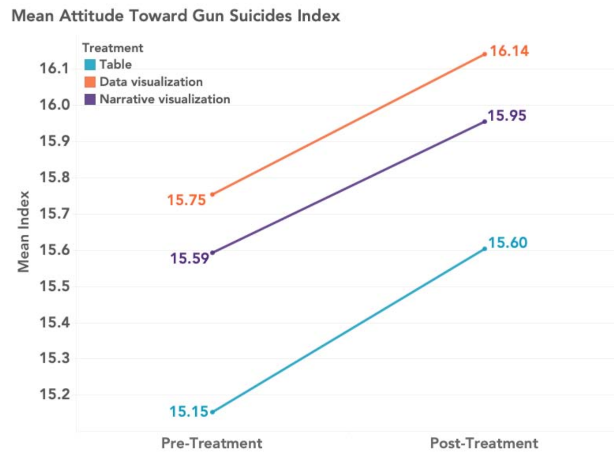

FIGURE 4. DIFFERENCES IN MEAN ATTITUDE TOWARD GUN SUICIDES INDEX BY TREATMENT

Education level and age. To understand how the treatments may have interacted with the demographic variables, we performed a four-way repeated measures mixed ANOVA to analyze the interaction effect between time, treatment, education level, and age range. The analysis indicated that the main effect for time was significant, but the interaction effect between time, treatment, education level, and age range was not significant. However, there was a significant interaction effect between time, treatment, and education level [F(2, 564) = 3.870, p = .021]. The interaction showed a small effect (ηp^2 = .014) on persuasion [34].

The findings suggest that there was a significant variation between treatments across education level, and the treatment and education level interaction contributed to the change in participants' attitude toward gun suicides. To understand why including the age range strengthened the significance of the time, treatment, and education level interaction, a Spearman's rank order correlation was used to determine the relationship between 600 participants' age and education level [35]. There was a strong, positive correlation between age and education level, which was statistically significant [r_s (598) = .151, $p < .001$]. The strong correlation between the two variables suggested that age helped to further elucidate the associations in the model.

III. Pairwise comparison

Since the interaction effect between time, treatment, and education level was significant, post hoc pairwise comparison was performed to evaluate the differences in persuasion by treatment across education level [27]. A Bonferroni correction was applied to account for multiple comparisons in repeated measures designs [27].

Data table. The pairwise comparison showed that the mean difference in attitude toward gun suicides was significant for the data table treatment across associate degree and below (p = .002) with a mean difference of 0.575. The mean difference in attitude toward gun suicides was also significant for the data table treatment across bachelor's degree and above (p = .012) with a mean difference of 0.435. The results indicated that the data table treatment had a significant effect on the participants' attitude toward gun suicides across both education levels (Figure 5).

Data visualization. The pairwise comparison showed that the mean difference in attitude toward gun suicides was significant for the data visualization treatment across associate degree and below (p < .001) with a mean difference of 0.724. However, the mean difference in attitude toward gun suicides was not significant for the data visualization treatment across bachelor's degree and above. The results indicated that the data visualization treatment had a significant effect on the participants' attitude toward gun suicides across those who had earned an associate degree and below, but the effect was not significant in those with a bachelor's degree and above (Figure 5).

Narrative visualization. The pairwise comparison showed that the mean difference in attitude toward gun suicides was not significant for the narrative visualization treatment across associate degree and below. However, the mean difference in attitude toward gun suicides was significant for the narrative visualization treatment across bachelor's degree and above (p < .001) with a mean difference of 0.572. The results indicated that the narrative visualization treatment had a significant effect on the participants' attitude toward gun suicides across those who had earned a bachelor's degree and above, but the effect was not significant in those with an associate degree and below (Figure 5).

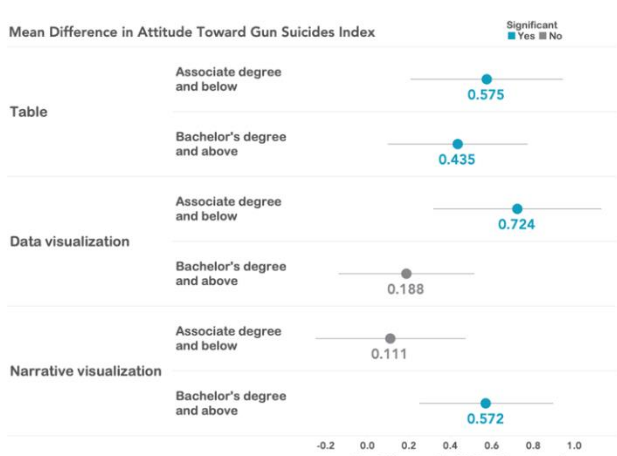

FIGURE 5. SIGNIFICANT MEAN DIFFERENCES IN ATTITUDE TOWARD GUN SUICIDES INDEX BY TREATMENT ACROSS EDUCATION LEVEL

DISCUSSION

In contrast to prior studies [6, 7, 17], the results of this study suggest that the data presentation alone did not account for the change in participants' attitudes. Further, the results suggest that the interaction between data presentation and education level contributed to the change in participants' attitudes. Additional analysis showed that each data presentation affected participants' attitudes differently across each education level (Figure 5). The data table (Figure 1) was persuasive across both education levels. The data visualization (Figure 2) was more persuasive in the associate degree and below group, and the narrative visualization (Figure 3) was more persuasive in the bachelor's degree and above group.

These findings represent a key consideration for designers and researchers who wish to communicate with broad audiences using narrative visualizations. Since news organizations regularly incorporate narrative visualizations into their journalism [2], designers and researchers may assume that these visualizations will effectively persuade the audience. While the results of this study suggest that narrative visualizations are persuasive in those with higher levels of education, the results also suggest that those with lower levels of education are more likely to be persuaded by a data table or a data visualization. To reach the largest audience across all education levels, designers and researchers should consider providing a data table alongside a narrative visualization.

The difference in the persuasive outcomes of the narrative visualization across education level may be explained by the relationship between education level and trust in the data presentation. Establishing trust in a visualization is one of the top challenges for designers [36]. This was also a prevalent issue in the study by Pandey et al. [6], which identified a lack of trust in the presented visualization as a common reason that participants were not persuaded. Trust is a fundamental aspect of visualization as it shapes how viewers interpret the information that is being communicated [37].

To understand how trust is established in visualizations, Lin and Thornton [38] investigated how visualization aesthetics affect trust. The researchers found that higher education levels correlated with increased trust in more aesthetically pleasing visualizations. Lin and Thornton [38] defined aesthetically pleasing visualizations as those incorporating the use of color, spacing, layout, and fonts, which were all integrated into our narrative visualization treatment using the visualization rhetoric framework [3]. The aesthetics of a visualization convey competence in the designer leading to increased trust in viewers with higher education levels [38]. The correlation between visualization aesthetics and trust in those with higher education levels may explain why the narrative visualization was persuasive amongst the bachelor's degree and above group but not the associate degree and below group.

CONCLUSION

Our findings extend prior studies by showing that the persuasive effect of the data presentation is dependent on the education level of the viewer. Specifically, we found that narrative visualizations are persuasive amongst those with higher levels of education, while data visualizations are more persuasive for those with lower levels of education. For designers and researchers, this is a key consideration as the persuasive effect of the data presentation is impacted by the audience's education level. The results of this study are useful to practitioners and researchers as the findings reveal how different presentations such as data tables, data visualizations, and narrative visualizations impact attitudes toward polarizing topics across education levels.

REFERENCES

[1] Centers for Disease Control and Prevention. [Online]. Available: https://covid.cdc.gov/covid-data-tracker/#datatracker-home.

[2] E. Segel and J. Heer, "Narrative visualization: Telling stories with data," *IEEE Trans. Visualization Comput. Graph.*, vol. 16, no. 6, pp. 1139-1148, 2010.

[3] J. Hullman and N. Diakopoulos, "Visualization rhetoric: Framing effects in narrative visualization," *IEEE Trans. Visualization Comput. Graph.*, vol. 17, no. 12, pp. 2231-2240.

[4] W. Rettberg "Ways of knowing with data visualizations," in *Data Visualization in Society,* M. Engebretsen and H. Kennedy (Eds.) Amsterdam University Press, 2020.

[5] J. Drucker, *Graphesis: Visual Forms of Knowledge Production*, Harvard University Press, 2014.

[6] Pandey et al., "The persuasive power of data visualization," *IEEE Trans. Visualization Comput. Graph.*, vol. 20, no. 12, pp. 2211-2220, 2014

[7] A. Tal and B. Wansink, "Blinded with science: Trivial graphs and formulas increase ad persuasiveness and belief in product efficacy," *Public Understanding Sci.*, vol. 25, no. 1, pp. 117-125, 2016.

[8] H. Kennedy et al., "Engaging with (big) data visualizations: Factors that affect engagement and resulting new definitions of effectiveness," *First Monday*, vol. 21, no. 11, 2016.

[9] C. Ware, *Information Visualization: Perception for Design*, Morgan Kaufmann, 2019.

[10] A.M. Treisman and G. Gelade, "A feature integration theory of attention", *Cogn. Psychol.*, vol. 12, no. 1, pp. 97-136, 1980.

[11] A. Treisman and S. Gormican, "Feature analysis in early vision: evidence from search asymmetries", *Psychol. Rev.*, vol. 95, no.1, p. 15, 1988.

[12] J. M.Wolfe et al., "The role of categorization in visual search for orientation," *J. Exp. Psychol.: Hum. Perception Perform.*, vol. 18, no.1, p. 34, 1992.

[13] H.M. Chen, "Information visualization," *Library Technol. Rep.*, vol. 53, no.3, pp. 1-30, 2017.

[14] I. Bogost, *Persuasive Games: The Expressive Power of Videogames*, MIT Press, 2017.

[15] R. Horn, *Information Design*, MIT Press, 2000.

[16] B. J. Fogg, *Persuasive Technology: Using Computers to Change What We Think and Do,* Morgan Kaufmann. 2003.

[17] J. Heyer et al., "Pushing the (visual) narrative: the effects of prior knowledge elicitation in provocative topics," in *Proc.2020 CHI Conf. Hum. Factors Comput. Syst.*, pp. 1-14, 2020.

[18] P. Dragicevic and Y. Jansen, "Blinded with science or informed by charts? A replication study," *IEEE Trans. Visualization Comput. Graph.*, vol. 24, no. 1, pp. 781-790, 2017.

[19] A. V. Maltese et al., "Data visualization literacy: Investigating data interpretation along the novice—expert continuum", *J. College Sci. Teaching*, vol. 45, no. 1, pp. 84-90, 2015.

[20] National Institute on Aging. *Global Health and Aging*. National Institutes of Health, 2011.

[21] M. Fan et al., "Understanding how older adults comprehend COVID-19 interactive visualizations via think-aloud protocol," *Int. J. Hum–Comput. Interact.,* vol. 39, no. 8, pp. 1626–1642. 2022.

[22] S. Palan and C. Schitter, "Prolific. ac—A subject pool for online experiments," *J Behav. Exp.l Finance*, vol. 17, pp. 22-27, 2018.

[23] Prolific, *Representative samples FAQ*, [Online], Available: https://researcher-help.prolific.co/hc/en-gb/articles/360019238413-Representative-samples-FAQ.

[24] Centers for Disease Control and Prevention, *WISQARS Fatal Injury Reports, National, Regional, and State, 1981-2020*, [Online], Available: https://wisqars.cdc.gov/fatal-reports.

[25] J. M. Jashinsky et al., "Media agenda setting regarding gun violence before and after a mass shooting," *Frontiers Public Health*, vol. 4, p. 291, 2017.

[26] A. Johnson in M. Allen (Ed.), "Reliability, cronbach's alpha," *The Sage Encyclopedia of Communication Research Methods,* vol. 1, pp. 1414-1417, SAGE Publications, 2017.

[27] J. P. Verma, *Repeated Measures Design for Empirical Researchers*, John Wiley & Sons, 2015.

[28] A. Zmyslinski-Seelig in M. Allen (Ed.), “Repeated measures,” *The Sage Encyclopedia of Communication Research Methods*, vol. 1, pp. 1432-1435, SAGE Publications, 2017.

[29] S. Card et al., *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann. 1999.

[30] R. Lengler, “How to induce the beholder to persuade himself: Learning from advertising research for information visualization,” *2007 11th Int. Conf. Inf. Visualization*, pp. 382-394, IEEE, 2007.

[31] J.L. Caivano and M. A. López. “How colour rhetoric is used to persuade: chromatic argumentation in visual Statements,” *Colour: Des. Creativity*, vol. 5, no. 11, pp. 1–11, 2010.

[32] E. R. Brumberger, “The rhetoric of typography: The persona of typeface and text,” *Tech. Commun.*, vol. 50, no. 2, pp. 206-223, 2003.

[33] S. B. Green and N. J. Salkind, *Using SPSS for Windows and Macintosh: Analyzing and Understanding Data*, Pearson, 2013.

[34] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, Lawrence Erlbaum Associates, 1988.

[35] J. Dellinger, “Correlation, spearman,” in *The Sage Encyclopedia of Communication Research Methods*, M.Allen (Ed.), SAGE Publications, 2017, vol. 1, pp. 273-275.

[36] J. Thomas and J. Kielman, “Challenges for visual analytics,” *Inf. Visualization*, vol. 8, no. 4, pp. 309-314, 2009.

[37] H. Elhamdadi et al., “Vistrust: a Multidimensional framework and empirical study of trust in data visualizations,” *IEEE Trans. Visualization Comput. Graph.,* vol. 30, no. 1, pp. 348-358, 2024.

[38] C. Lin and M.A. Thornton, “Fooled by beautiful data: Visualization aesthetics bias trust in science, news, and social media,” *PsyArXiv*, 2021.

About the Authors

Dr. Matthew Chambers is Executive Director of Visual Analytics and a Lecturer at Clemson University. He holds a Ph.D. in Rhetorics, Communication, and Information Design from Clemson University.

Dr. Bryan Denham is a Professor in the Department of Communication at Clemson University. He holds a Ph.D. in Communications with a minor in Applied Statistics from the University of Tennessee.