Abstract and Metaphoric visualization of emotionally sensitive data

by

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B.Tech., Meerut Institute of Engineering and Technology, India, 2016

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ABSTRACT

Standard visualizations such as bar charts and scatterplots, especially those representing qualitative, emotionally sensitive issues, fail to build a connection between the data that the visualization represents and the viewer of the visualization. To address this challenge, the information visualization community has become increasingly interested in exploring creative visualization techniques that could potentially help viewers relate to the suffering and pain in emotionally sensitive data. We contribute to this open question by investigating whether visualizations that rely on metaphors (i.e., that involve existing mental images such as a tree or a person image) with some emotional connection can foster viewers' empathy and engagement with the data. Specifically, we conducted an empirical study in which we compare the effect of visualization type (metaphoric and abstract) on people's engagement and empathy when exposed to emotionally sensitive data (data about sexual harassment in academia). We designed a metaphoric visualization that relies on the metaphor of a flower symbolizing life, beauty, and fragility which might help the viewers to relate to the victim, build some emotional connection, and an abstract visualization that relies on purely geometric forms with which people should not have any existing emotional connection. In our study, we found no clear difference in engagement and empathy between metaphoric and abstract visualization. Our findings indicate that female participants were slightly more engaged and empathic with both visualizations compared to other participants. Additionally, we learned that measuring empathy in a data visualization is a complex task. Informed by these findings on how people engage and empathize with metaphoric and abstract visualization, newer and improved visualization and experiences can be developed for similar emotionally sensitive topics that are emotionally charged and fear-provoking.

Contents

List of Tables

List of Figures

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My family and **my partner Aakash Tyagi,** for motivating and believing in me.

DEDICATION

I dedicate this project to my parents and my partner.

For their endless love, support, and encouragement.

Chapter 1

Introduction

In recent years, information visualization has become a popular method for effectively conveying messages and spreading awareness about subjects like sexual harassment, child abuse, suicide, and other topics that may affect people's feelings, ideas, attitudes, and values. Standard visualizations like bar charts, pie charts, etc. represent quantitative information well but they fail to connect viewers with the human sufferings that this data describes [1]. Additionally, as per psychologists, these standard visualizations suffer from a "psychic numbing effect," or "compassion fade," which describes how our capacity for empathy decreases as the number of people suffering rises. Mark Twain originated the quote "As rise higher and higher to the sky, they become in the same proportion more and more inexplicable" [2]. These challenges with data involving sensitive sentiments call for the need of designing and evaluating visualization techniques that could form a human connection. The concept of humanizing data was popularized by Giorgi Lupi and Stefanie Posavec in their book 'Dear Data' [39]. We think it is important to foster data-driven empathy and engagement in the visualization to enable viewers to form a human connection with emotionally sensitive data and explore the invisible emotions and feelings involved in the dataset.

In fact, other data visualization researchers [10, 11] have studied how human-like visuals or "anthropographics" in visualizations can elicit empathy or humanize the data. Although these previous studies did not demonstrate the clear benefits of anthropographics, anthropographics is only one approach used to eliciting empathy with data. The idea that data visualizations built with creative and engaging visual representations could evoke viewers' empathy and engagement has some supporters, while others have expressed their doubts and concerns [4]. Another popular approach to humanizing data consists of relying on metaphoric visuals to symbolize a certain entity or concept. Several visualization designers [12,13,14] have developed data visualizations using this metaphoric approach for emotionally sensitive data, such as using a flower petal to represent a day of a child's illness and using metaphors of trees, waves, stars, and fireflies to represent different suicide ways of people suffering from depression and pain. However, little research has examined the effect of this metaphoric approach on viewers. Further research is required to understand how these creative visuals affect viewers' responses to a visualization. In this report, we contribute to addressing the complex topic of the role visualization design might play on empathy and engagement of people using the metaphoric-focused approach, by conducting an empirical study that compares metaphorical and abstract visualization representing emotionally sensitive data.

1.1 Motivation

The motivation behind this project grew out of a desire to explore non-traditional visualizations for emotionally sensitive data that may help in spreading awareness in an impactful manner in the future. We were inspired by metaphoric visualization [12, 13] using real-world entities with some emotional connection as a potentially effective technique for representing emotionally sensitive information compared to the traditional and abstract visualizations. Conceptual Metaphor Theory (CMT) indicates that metaphor is the fundamental mechanism to shape the way we think and act [8]. That is one reason why visual metaphor is a commonly used technique in the advertising and editorial design world where the designer's goal is to convince the readers of something.

1.2 Contribution

The primary goal of the project is to understand whether a metaphoric representation of an emotionally sensitive dataset can lead to more engagement and empathy from the viewers compared to the abstract representation. To achieve this, the contributions of the project are as below:

1. The design and implementation of one metaphoric and one abstract visualization using the "sexual harassment in academia" dataset [1], with similar visual channels to encode data dimensions.
2. A web-based experiment to learn how people empathize and engage with the implemented metaphoric and abstract visualization.

3. The analysis and evaluation of the experiment results to compare the metaphoric and the abstract visualization.

We formulated two hypotheses for the experiment:

H1: The metaphoric visualization will elicit more empathy for emotionally sensitive data compared to abstract visualization.

We formulated H1 thinking that the existing mental images in the human brain of relatable metaphors and their understanding would force the users to connect and empathize more with the victim. A similar hypothesis was also tested in previous studies [10, 11].

H2: The metaphoric visualization will elicit more engagement for emotionally sensitive data compared to abstract visualization.

We formulated H2 thinking that the creative and pleasing aspect of a relatable metaphor could counteract the fear-proving nature of the emotionally sensitive data, making it more appealing to the user and would therefore encourage interactivity. We took inspiration for this hypothesis from existing visualization projects and studies [12, 13, 32].

The intended primary audience for this project is the visualization research community interested in exploring the benefits of metaphoric visualizations compared to abstract (e.g., circles, squares, and other kinds of shapes) or traditional visualizations (e.g., pie charts, bar charts, etc.) for similar emotionally sensitive datasets.

1.3 Outline

The project report is organized as follows:

Chapter 1 provides a brief introduction to the importance of data visualization for emotionally sensitive data. It includes the motivation of the project, research hypotheses, and project contributions.

Chapter 2 discusses the related work and background knowledge related to metaphoric and abstract data visualizations.

Chapter 3 describes the design and implementation process of the metaphoric and the abstract visualization we selected. It discusses the data, processing of raw data, design journey, visual encodings, and interactivity along with implementation details.

Chapter 4 describes the experimental design, pilot study feedback-based improvements, and the execution of the main experiment.

Chapter 5 presents the analysis and discussion of the experiment results. It includes a comparison of the metaphoric and abstract visualizations based on measures of participants' empathy and engagement.

Chapter 6 concludes the report and provides suggestions for future work.

Chapter 2

Related Work

2.1 Role of Empathy and Engagement in Data Visualization

As we implemented this project, we first explored the factors needed in a visualization that can help the audience to connect more with the data it represents. We came across empathy as a means for connecting the content with human understanding. Additionally, no matter how appealing a visualization is designed, it is of little value unless it engages users. Therefore, we aimed to foster engagement and empathy with our visualizations.

2.1.1 Empathy

Empathy is broadly defined as "an effective response appropriate to someone else's situation rather than one's own" [5]. Specifically, the term empathy is considered to have two main dimensions. It can be defined either as cognitive empathy, in relation to understanding others' feelings or states [16], or as individual emotional arousal or concerns towards other feelings or experiences [17] called affective empathy. In this report, the generic use of empathy refers to emotional empathy. In recent research [3, 10, 11, 12, 13, 14] to foster emotional empathy, visual designers have used narratives, anthropographics and conceptual metaphoric visuals in the data visualization. It has been hypothesized that these techniques accompanied by future research could promote empathy through data.

To measure empathy in prior studies, researchers have used multiple approaches like the picture/storytelling procedure [20] and asking participants to verbally indicate how they feel, show how empathy can shift donation preferences [10, 11], and use self-reporting questionnaires to understand a person's subjective responses [16, 17, 18, 19]. We further researched the self-report methodology to evaluate emotional empathy because of its appropriateness of understanding a person's subjective responses. Figure 2.1 shows the three most popular self-reporting questionnaires that are used to measure different types of empathy.

Empathy measure	Type	Description	Subscales	Example
HES: Hogan's empathy Scale (Hogan, 1969)	Affective	64 items, T/F scale	N/A	I enjoy the company of strong-willed people.
QMEE: Questionnaire Measure of Emotional Empathy (Mehrabian and Epstein 1972)	Affective	33 items, 9 points Likert scale (7 subscales)	1. Susceptibility to emotional contagion 2. Appreciation of the feelings of unfamiliar and distant others 3. Extreme emotional responsiveness 4. Tendency to be moved by others' positive emotional experiences 5. Tendency to be moved by others' negative emotional experiences 6. Sympathetic tendency 7. Willingness to be in contact with others who have problems	The people around me have a great influence on my moods
IRI: Interpersonal Reactivity Index (Davis 1983)	Cognitive, Affective	28 items, 5 points Likert scale (4 subscales)	1. Perspective Taking 2. Fantasy 3. Empathic Concern 4. Personal Distress	I tend to lose control during emergencies.

Figure 2.1: Popular empathy measuring questionnaires

In the process of analyzing these questionnaires, we came across the MDEES: Multidimensional Emotional Empathy Scale developed by Caruso and Mayer (1998) [19] to measure emotional empathy. It has six subscales based upon an emotional view of empathy: Empathic Suffering (ES), Positive Sharing (PS), Responsive Crying (RC), Emotional Attention (EA), Feeling for Others (FO), Emotional Contagion.

2.1.2 Engagement

The goal of user engagement in visualization is that the viewers should be willing to view or interact with the visualization more actively and spend more time connecting with it. The concept of engagement has been described as related to the flow of interaction that results in satisfying and pleasurable emotions like curiosity, surprise, and joy [9]. One of the common techniques to foster engagement in data visualization is to force users to interact with it. Yi et al. [21] have defined the following seven general categories of interaction techniques based on user intents in information visualization:

1. **Select**: mark something as interesting
2. **Explore**: show me something else
3. **Reconfigure**: show me a different arrangement
4. **Encode**: show me a different representation
5. **Abstract/Elaborate:** show me more or less detail
6. **Filter:** show me something conditionally
7. **Connect:** show me related items

We consider these interaction techniques to foster engagement in our visualization's implementation. To assess user engagement, various disciplines have used different approaches like collecting behavioral indicators like mouse clicks, user movements, time spent, etc. as an indicator of user subjective experience [22]. Another popular approach is to use questionaries like (IEQ: Immersive Experience Question) [23], VisEngage [24], etc. We found that the VisEngage self-assessment questionnaire is one of the more detailed, complete, and relevant questionnaires to measure user engagement. It covers 11 engagement characteristics that had the highest frequency in the literature: Aesthetics, Captivation, Challenge, Control, Discovery, Exploration, Creativity, Attention, Interest, Novelty, and Autotelism. We think these characteristics are more relatable to a user's interaction with data visualization.

2.2 Creative data visualization techniques

Various non-traditional visualization designs were explored in our research journey that either aim to elicit empathy, and engagement or balance the disturbing part of the emotionally sensitive data by making it look more appealing. In our research, we found out that anthropographics (human-like visuals) and conceptual metaphoric are among the popular approaches used by researchers and visual designers to study or visualize the emotionally sensitive datasets.

2.2.1 Using Anthropographized visuals

The practice of visualizing data about people in a way that makes a direct connection with the audience is called anthropographics. Boy and colleagues [10] coined "anthropographics" as an abbreviation for anthropomorphized data graphics, using human-like symbols for data visualization. Moreover, Boy and his colleagues were the first to experiment with how visualizations elicit empathy using anthropographics. They conducted several experiments to test if anthropographics would increase empathy in viewers using data related to human rights issues like poverty, displacement, access to water, and education. Participants' responses were measured by how much hypothetical money they donated after the experiment. As opposed to their expectations, they found that standard charts (e.g., pie charts) had similar effects on empathy.

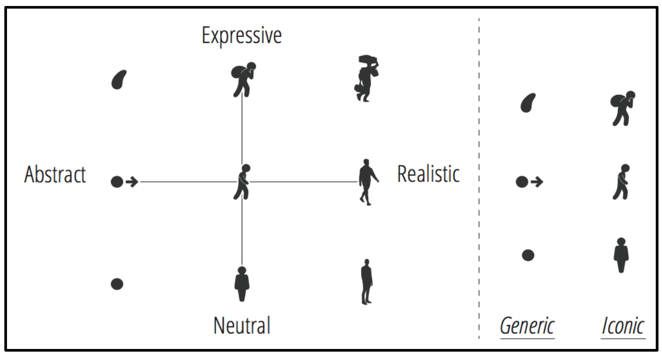


Figure 2.2: Screenshot from anthropographics experiment by Boy and his colleagues [10]

Figure 2.2 illustrates the incorporation of realism (human figure) and expressiveness (like an icon showing a migrant with a bag on his head) in the anthropographics experiment by Boy and his colleagues.

Further, Morais and colleagues [11] expanded the initial anthropographics design space outlined by Boy and colleagues [10] from low or intermediate granularity and partial authenticity to maximum granularity and full authenticity. To do so, they expanded four design dimensions: granularity, specificity, coverage, and authenticity to seven dimensions of design by adding realism, physicality, and situatedness. The design choice of testing the experiment was kept the same as Boy and his colleague's work [10]. They conducted two experiments on their larger vision of human-like data graphics using the data about migrants in Southeast Asia who suffered accidents or attacks in 2018. Once again, the expectation didn't quite pan out, as there was either no clear conclusion or only a small improvement. Lead author Luiz Morais reported, "It seems that anthropography might slightly increase empathy but not compassion".

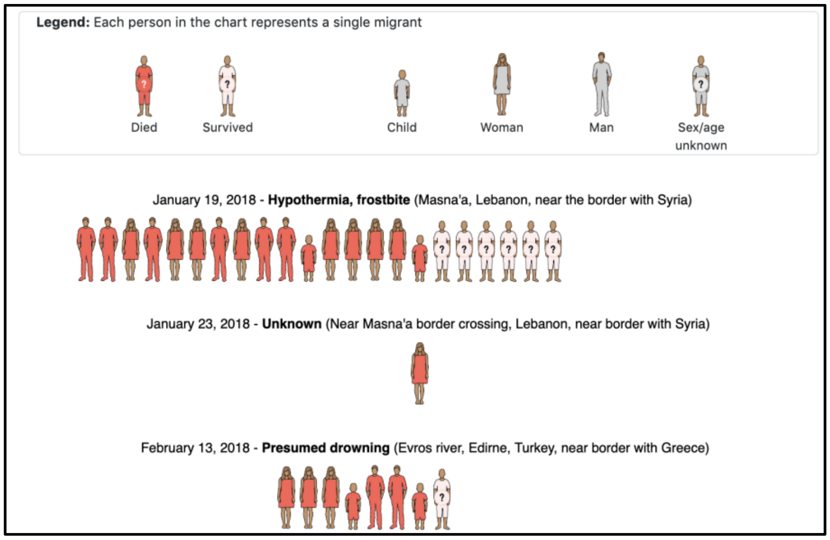


Figure 2.3: Screenshot from anthropographic experiment by Luiz Morais and his colleagues [11]

In Figure 2.3, each human visual represents a real victim that tried to cross a border in the Middle East. Participants could scroll the page to see the victims of incidents up to December 2018.

2.2.2 Using Conceptual Metaphoric visuals

A conceptual metaphoric visual refers to a graphic or a figure form of a real-world entity like a person, place, thing, or idea that suggests a particular association or similarity. For example, a tree is a common metaphor used to represent hierarchical relations in books. A metaphor can also be viewed as a device by which one entity or concept is understood in terms of another. Attributes/concepts of a source entity are selectively mapped onto a target entity (something that you are already familiar with), and the source helps to explain the target [8]. According to Lakoff & Johnson [8], it is the foundation of human thought. Visual metaphors are often used to influence outcomes of attention, memory, and attitude change [7]. Therefore, when metaphors are intentionally employed, the designer is making use of an existing human mental image or model. In the data visualization community too, the use of metaphor is often used as a promising means of creating human-centered data visualizations [12, 13, 14, 26, 27]. Next, in this section, we will discuss a few related visualizations to illustrate the breadth of the visualization work that has been done related to metaphoric visualizations of emotionally sensitive datasets.

A view on despair - Sonja Kuijpers, a renowned Information designer, created a data visualization project called 'A view on despair' [12]. Her struggle, depression, and pain pushed her to try to commit suicide. She was motivated to create a visualization on this sensitive matter based on her struggle as well as those of other people in her circle who committed suicide. She began by sketching how various ways of suicide would convert to visuals without being brutal. Contrary to the social issue, the final visualization looks beautiful and serene yet shows the extent of devastation at the same time. She chose metaphor-like trees, waves, stars, buildings, fireflies, etc. to represent suicide incidents by hanging, overdoses, drowning, jumping from a height, or in other ways. She calls it 'data art' as a method that experiments with form and style. Her approach was inspired by the idea that empathy is what a human in pain or suffering needs, not sympathy.

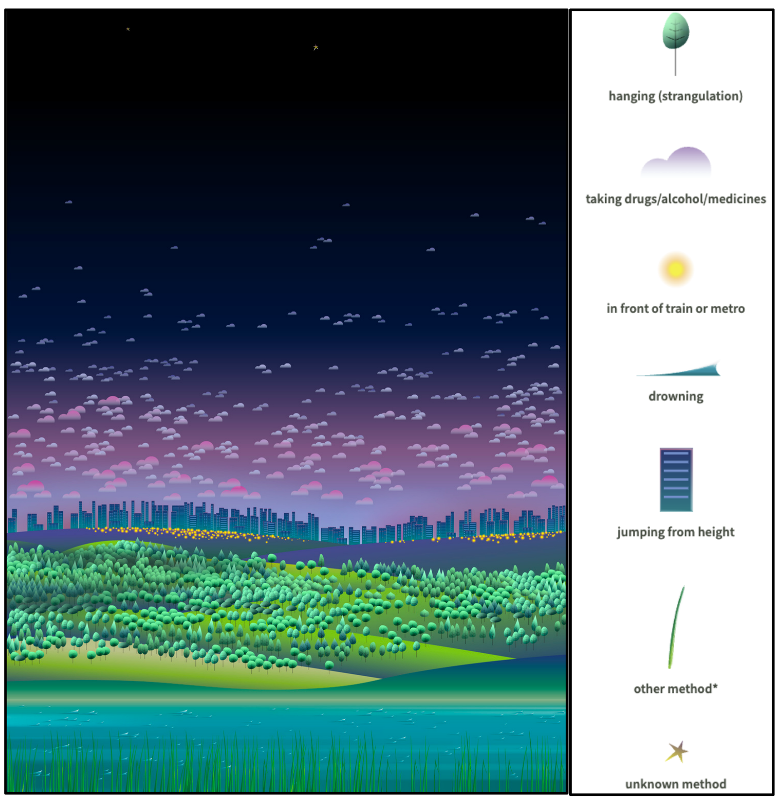


Figure 2.4: A view on despair by Sonja Kuijpers [12]

Link - http://www.studioterp.nl/a-view-on-despair-a-datavisualization-project-by-studio-terp/

Bruises: The Data We Don't See - Giorgi Lupi, an information designer, worked in collaboration with Kaki King, a musician, composer, and friend. Together, they created a heart-touching data visualization called 'Bruises – The Data we don't see' [13] using a combination of sounds and visuals to communicate the missing information from clinical records. The visualization represents the progress of a child's illness coping with an auto-immune disease as well as the emotional journey of the family. The visualization is created with the daily observations of symptoms of the child, such as the platelet counts, the bruises on the skin, the intensity of the bruises, etc. over 4 months. Each petal is a metaphor representing each day. Red dots are platelet counts (the disease destroys them), and the color is used to represent various events like bleeding, medications, or positive feelings. As seen in figure 2.5, these details were presented in floral petals to show a visual metaphor of being beautiful yet fragile. The text around the petals is the mother's notes about the day.

Figure 2.5: Bruises - the Data We Don't See, by Giorgi Lupi [13]

Link -http://giorgialupi.com/bruises-the-data-we-dont-see

Loneliness through the lens of data visualization - Sananda Dutta's thesis on 'Empathy through Data' [14] investigates a creative way of representing the issue of loneliness faced by the people living in Ontario during the COVID-19 pandemic's first wave using data visualizations and narrative storytelling. As can be seen in figure 2.6, she represented the whole visualization as a scenic garden lake and used flowers as a metaphor for life, which is quite similar to the design choices we made in our project. The color of the flower represents the gender, the stem of the flower represents the age group it belongs to, the state of flower-like opening, closing, blooming represents the different states of depression faced by the people and the flower standing position represents the different state of loneliness faced by an individual. Around 28 participants shared their experience and wisdom regarding the design choices through a survey. 80% out of total candidates found the representation apt for representing the issue and the top 5 used words were lonely, emotional, calm, gloomy, and hopeful which cover both positive as well as negative emotions.

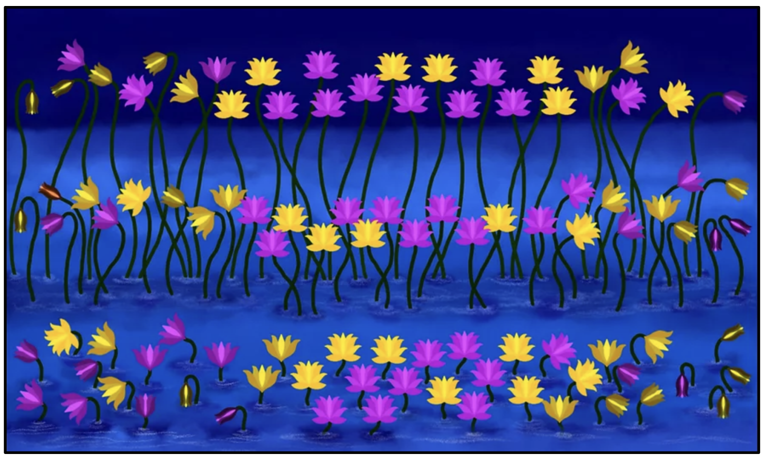


Figure 2.6: Loneliness through the lens of data visualization by Sananda Dutta [14]
Link - *http://openresearch.ocadu.ca/id/eprint/3331/*

2.2.3 Using Abstract visuals

Abstract graphics are visuals that have no visual relationship to a real subject like line, circle, square, etc. Next, in this section, we will discuss a few visualizations to illustrate the work that has been done related to abstract visualizations of emotionally sensitive datasets.

U.S. Gun Deaths in 2010 and 2013 - Periscopic created an inspiring interactive data visualization on the sensitive issue of deaths by guns in the US in 2010 and 2013 [15]. A person is represented by a line. The orange part represents the period lived and the gray part represents the estimated years stolen from the person. The audience can select the year and filter the data by sex, age, region, and time.

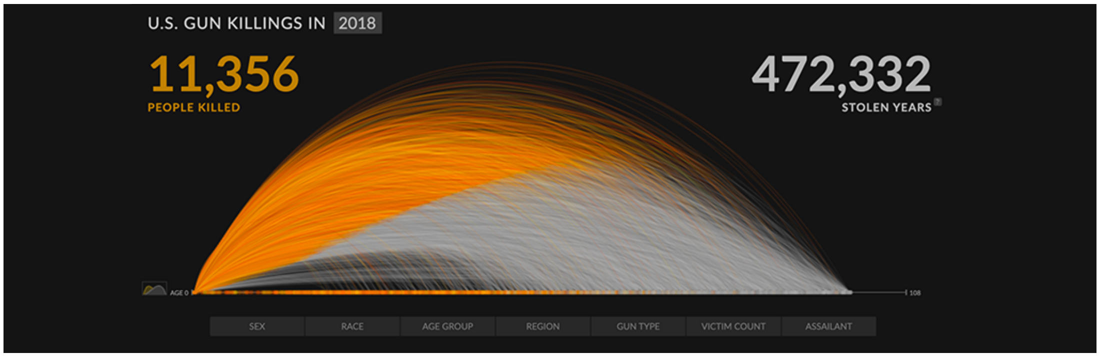


Figure 2.7: U.S. Gun Deaths in 2010 and 2013 interactive visualization by Periscopic [15]

Link - https://guns.periscopic.com/

Visualizing Foster Care Instability - The data visualization created by Robert Latham shows the movements of foster youth in and out of placements of various types and their related durations in Florida's foster care system [36]. Every dot on the map represents one or more placements of a child. Dot color is used to show the type of placement, the size of the dot shows the time spent by the child there, and the lines show the movements from placement to placement. Figure 2.8 shows a child with the second most number of placement entries (286 lines) [37]. The visualization illustrates that foster care lacks stability and this overburdened system puts kids at the risk for further psychological damage.

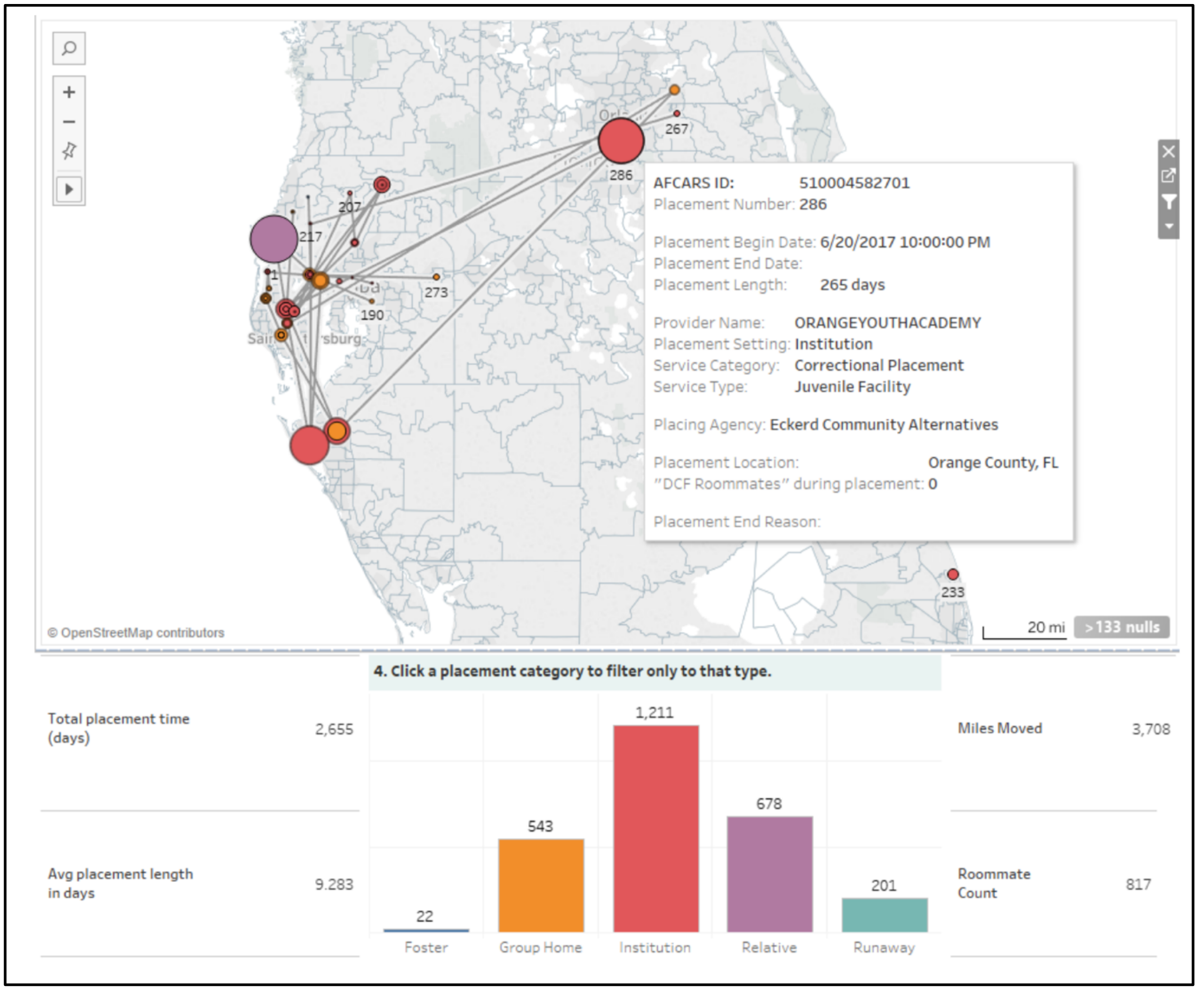


Figure 2.8: Screenshot of data visualization on Foster Care instability by Robert Latham [36]

Link- https://robertlathamesq.org/this-is-not-okay-visualizing-foster-care-placement-instability

Police Shootings - The data visualization by Chris Love represents the proportion of black people killed by police in America than white people. Each polygon represents a different state of America, and the color saturation of the polygon represents the proportion of black people killed compared to white people. Each polygon shows the absolute number of 10 or more black death that happened in a state since 2015.

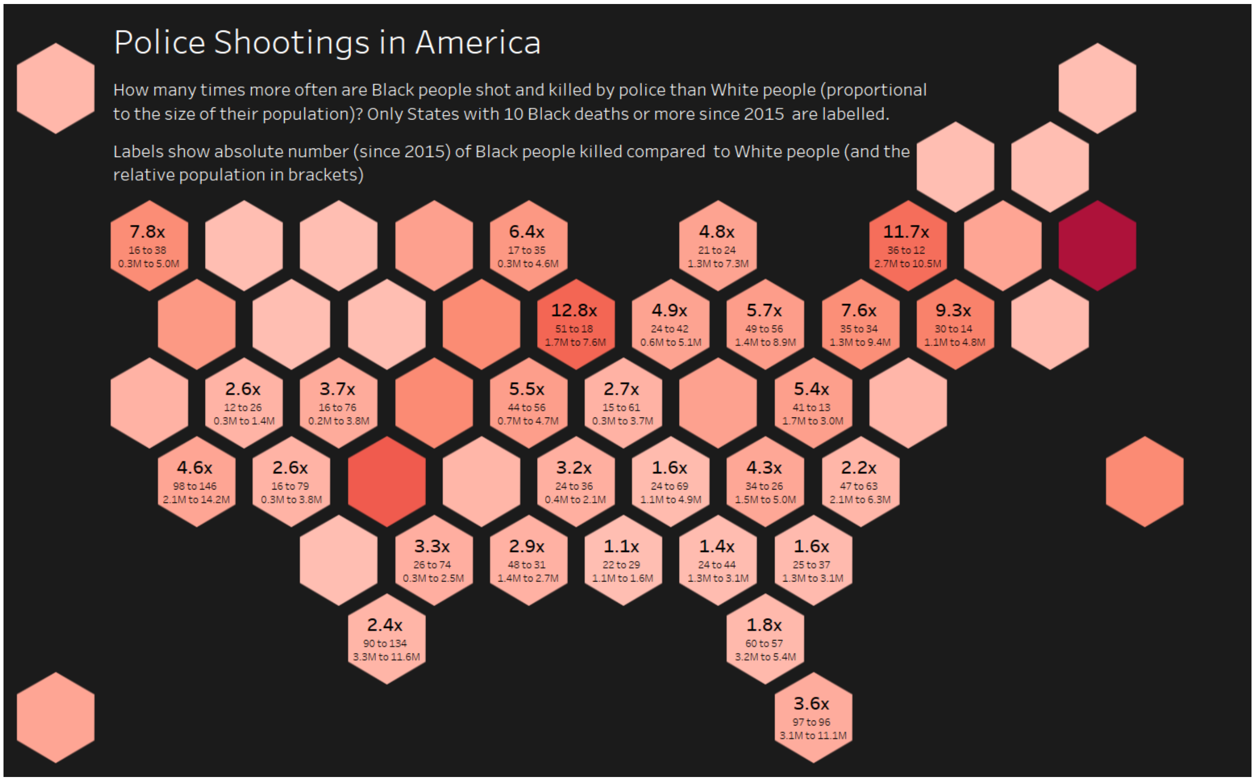


Figure 2.9: Police Shootings in America data visualization by Chris Love [38], *Link-https://public.tableau.com/app/profile/chrisluv/viz/PoliceShootings_15923509663370/PoliceShootings*

Chapter 3

Design and Implementation

Before designing and implementing a visualization, there is the necessary step of understanding and cleaning the data. The following section discusses the raw data processing followed by the design and implementation journey of the metaphoric and abstract visualizations.

3.1 Data

According to the Cambridge dictionary [6], emotionally is defined as "in a way that is full of strong feelings" and sensitive is defined as "easily upset by the things people say or do, or causing people to be upset, embarrassed, or angry". In the context of this project, we call an "emotionally sensitive dataset" a dataset that involves strong suffering emotions and is concerned with the emotional well-being of an individual. Several topics like drugs addiction, sexual harassment, and gender inequality, were explored to be considered as a base for this project. We eventually selected the "Sexual Harassment in Academia" dataset to examine the effect of metaphoric visualization on viewers' empathy and engagement. Self-reported datasets such as these are rare, and the right kind of visualization may help to communicate this vital information among the community. The "Sexual Harassment in Academia" dataset is a collection of sexual harassment incidents in academia collected through an anonymous crowdsourced survey, "Sexual Harassment in the Academy". The survey was created by Dr. Karen Kelsky, a former anthropology professor, in late 2017. This survey provided a space for victims of sexual harassment to voluntarily report their assault without any fear of repercussions. This data is highly personal and sensitive. More than 2000 testimonies have been collected since the launch of the survey and it was closed recently because of hacking concerns. Dr. Kelsky has released the data publicly in a spreadsheet [1].

3.2 Raw Data Processing

We conducted exploratory data analysis to fully understand the selected dataset and identify the possible attributes of a person's testimony that could be visualized.

3.2.1 Feature selection and data standardization

The “sexual harassment in Academia” dataset [1] consists of 2438 rows and 13 columns. We found that it includes only two categorical variables (multiple-choice options):

1. Gender of the perpetrator (woman/man/non-binary/unsure/various/ other)
2. Type of institution (small liberal arts college/Regional Teaching College/ Elite Institution/Ivy League/Other R1 etc.)

Other fields in the data were open-ended submissions with free text about:

1. Event description (e.g. I was a Ph.D. student in my final year ....)
2. Target status (e.g., student, professor, etc.)
3. Perpetrator status (e.g., professor, fellow graduate student, etc.)
4. Name of the institution (e.g., University of ....)
5. Academic discipline (e.g., arts, humanities, etc.)
6. Institutional response (e.g., none, not reported, not aware of, etc.)
7. Institutional/career consequences for the perpetrator (None, not known, etc.)
8. Impact on your career (e.g., left the course, not sure, etc.)
9. Impact on your mental health (e.g., depression, anxiety, etc.)
10. Impact on life trajectory/choices, and others (e.g., drugs, alcohol, etc.)
11. Other comments (Thank you for the survey, I have heard other incidents......, etc.)

The initial exploration of the data revealed that the dataset was very unstructured and unpredictable as it was collected through an online survey, which allowed free text and optional fields. Therefore, the dataset needed a certain amount of cleaning and standardization before it could be analyzed. To filter out the dataset, an informal brainstorming session was conducted at the VIXI (Victoria Interactive eXperiences with Information) lab at the University of Victoria. In the 30 minutes session, four participants related to the data visualization field were asked to draw up to 4 visualizations on paper using the data fields they are most interested in investigating. We found that the most chosen fields to draw visualization were perpetrator status, victims' status, and academic discipline. Furthermore, we placed a higher priority on data fields containing more personal information, like the event description, and the fields with a low unpredictable response pattern, like the gender of the perpetrator and type of the institute. Considering these factors and the results of the brainstorming session, we selected 6 fields for the visualization: event description, perpetrator status, victims' status, gender of the perpetrator, academic discipline, and type of institution. The selected fields were renamed as follows:

- Event description -> Event
- Perpetrator status -> Harasser rank
- Victims' status -> Victim rank
- Gender of the perpetrator -> Harasser gender
- Academic discipline -> Victim field of study
- Type of institution -> Victim institute type

Cleaning and standardization of data were performed on Jupyter notebooks using the Python programming language and data manipulation libraries like pandas. To handle missing values, rows that contained null values were dropped. This is not ideal, but a reasonable approach for this project given that we only needed a small set of incidents to display in the final visualization. Next, we analyzed all selected fields one by one for data standardization. We decided not to clean nor transform the event description field to maintain the originality of a person's testimony. For the other selected fields, we converted the freeform text data into categorical data. As most of the columns were user-determined text fields, the data in each column was hard to group because of the multiple labels to describe the same thing (> 20 similar names of the same thing in some cases). For example, graduate students can address their status as MSC, MBA, graduate student, grad student, and other similar labels. To standardize these attributes, we used a keyword/rule-based matching approach. We created a keyword pool for each field based on the existing unique values and their instance count in the data. Then a rule-based matching was executed to rename similar labels with a unique label. As a result of this implementation, the previous example with status MSC, MBA, graduate student, grad student, and other similar labels were all renamed to graduate students. After each instance was consistently labeled, we excluded all non-match values with 3 or fewer total instances. A total of 1220 rows were left after data cleaning and standardization. The standardized data dimension had the following distinct categories:

- Harasser rank – undergraduate student, graduate student, staff, faculty, chair/dean/head
- Victim rank - undergraduate student, graduate student, staff, faculty, chair/dean/head
- Harasser gender – male, female, other
- Victim institute type – research institute, elite institution, regional college, more than one institution, other type of school.
- Victim field of study – social sciences, natural sciences, formal sciences, applied sciences, and humanities.

It was particularly challenging to standardize the victim's field of study, as the victims could have either filled a more generic academic discipline in the survey like humanities or one that is more specific, like theater. To categorize victims' field of study, along with the data values, we referred to the academic discipline hierarchy structure [35].

3.2.2 Data Sampling

A good data sample is the one that represents the original dataset. To implement data sampling, a python recursive function was created which randomly selected 70 stories from the standardized dataset and iterated until the following conditions were passed:

a) the selected sample set includes all unique values for each data field.
b) The difference in the unique value composition of a field with respect to the original dataset is smaller than 5%.
c) The event description of each story contains no more than 400 words and no fewer than 10 words. This rule was included later considering the visualization experiment design and timing of the experiment: stories should be long enough that they are interesting to read, and they should be short enough that participants can read the incidents in a reasonable amount of time and complete the study within the expected time frame.

After getting the sample dataset, it was manually analyzed. Since the data includes some inconsistencies as it was entered as free text, there was no better way than incorporating human judgment in this selection process. We found out that many reported incidents were of sexual discrimination, not sexual harassment, in the dataset. We replaced those incidents with a data row having similar values to maintain representativeness. In the end, 62 incidents were selected to display in the visualization. Figure 3.1 illustrates that the selected sample dataset is representative of the original data set. It illustrates visually the data standardization process and confirms the similar proportions of each group within the standardized data and the selected data sample. For example, the total area of the purple rectangles in victim rank in the original dataset is comparable to that of the large purple rectangle in the standardized dataset, and it is also like that of the large purple rectangle in the selected sample. Except for the black color, the color used in the different charts does not have any specific mapping but represents distinct data values. The black rectangles in the different charts represent the data values with three or fewer occurrences, which we were unable to classify. In the selected sample these values were dropped.

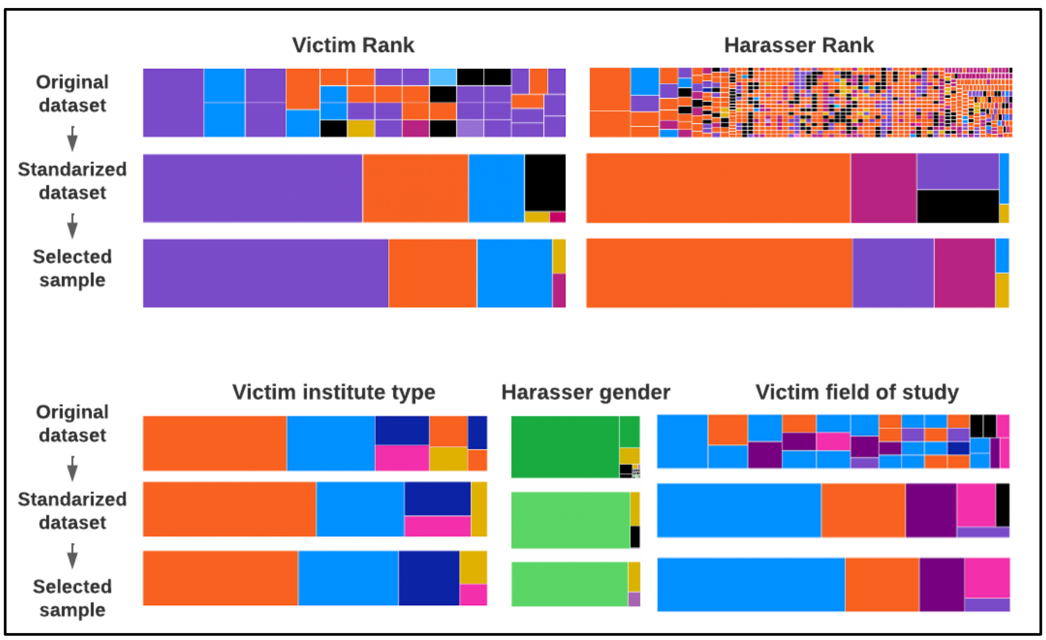


Figure 3.1: Abstract representation of data standardization and sample selection

After reviewing the visualization charts of data standardization, a final inspection was done, which confirmed that the distribution of values in the selected sample corresponded to the distribution in the original dataset and consisted of the sexual harassment event description, that they were complete, and that they were not too short and not too long.

3.3 Design Journey

The design journey began with the metaphoric visualization followed by the abstract visualization.

3.3.1 Metaphoric Visualization

We started the metaphoric visualization design journey thinking around the following questions:

- How can we make the emotionally sensitive data visualization appealing to the audience maintaining its originality?
- What kind of conceptual metaphor can give more voice to the visualization compared to abstract or more traditional visualization like a pie chart, or bar chart?

With these questions in mind, we took inspiration from some of the prior data visualization projects [12, 13] and chose a flower visual as the conceptual metaphor to represent the victim in the metaphoric visualization. The flower as an entity symbolizes life, beauty, and fragility which might help the viewers to refer to the victim. We are considering that the beauty and appealing aspect of the flower visual can help to balance the fear-proving nature of the emotionally sensitive data. In the context of this project, the metaphoric visualization flower represents a beautiful yet fragile human life. Our goal is to make use of the existing human mental image and understanding of flowers to force connect with the victim. Additionally, the visual elements of the flower-like color of the flower, the shape of the petal, the size of the petal, its orientation, etc. open the opportunity to encode many different dimensions of the data.

Drawing is a natural way for domain experts to express their visualization goals. As part of the conceptual process, we conducted a few rounds of free-hand sketches of flowers to give shape to our ideas of the visuals for metaphoric visualization. Examples of the hand-drawn sketches prior to the implementation of metaphoric visualization are shown in Figure 3.2, where some of the sketches are scrawled and the other half are colored.

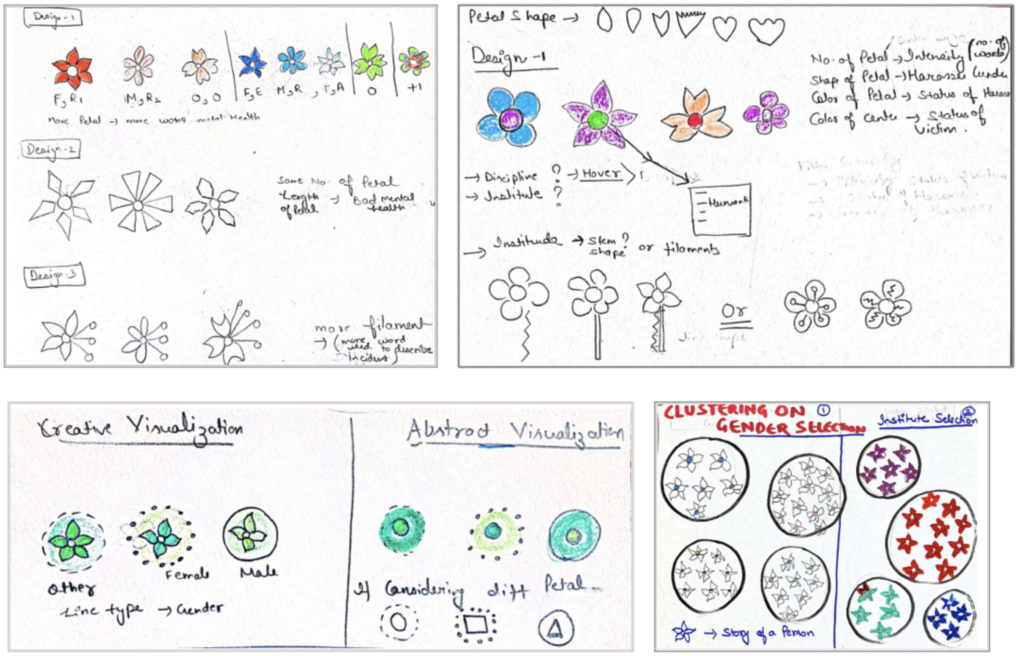


Figure 3.2: Hand-drawn sketches in the design journey of the metaphoric visualization

After analyzing all the designs, we conclude with the idea that the complete incident will be represented by a flower (graphical mark for the victim) inside a circle (graphical mark for the harasser). The narrative behind the selected design is that the victim (flower) is trapped by the harasser and the trauma of the incident (circle). The flowers were randomly given 5-8 petals to introduce some randomness in the metaphoric visualization.

3.3.2 Abstract Visualization

To choose the visual for the abstract visualization another informal brainstorming session was conducted at the VIXI (Victoria Interactive eXperiences with Information) lab at the University of Victoria. Eight lab members knowledgeable in data visualization participated in the 30 minutes session. They were presented with the project's background, metaphoric design and were asked to create several abstract designs using similar data fields and narratives as used for the metaphorical visualization design.

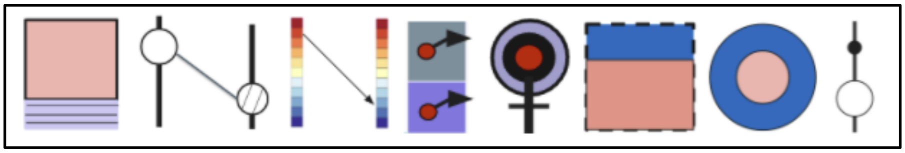
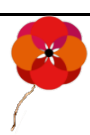


Figure 3.3: Examples of abstract visuals from the brainstorming session

We initially chose a square visual for a victim based on the repetition of design in the brainstorming session and it was visually less complex. However, later in the implementation phase, we changed the square visual to a polygon because different shapes of polygons can represent the victim's different fields of study.

3.4 Visual Encoding

In information visualization, visual encoding is the process of assigning data fields to visual channels like shape, size, color, etc. for a clear, quick, and effective understanding of the data by viewers [34]. To choose appropriate visual encodings for the metaphoric visualization we first studied how flower visual is used in various existing data visualization projects. The summary of our research on flower visual encoding is shown in Table 3.1. The X indicates that the respective visual encoding was not used in the data visualization to represent the data.

	Project	**Metaphor**	**Petal**			**Flower**		**Stem**	**Seed (Center of flower)**	**Interactions**
			Shape	**Color**	**Density**	**Color**	**Size**			
1	Blooming Countries [25]	 Country	**X**	Type of resource	**X**	**X**	Compare countries by their resources	**X**	**X**	**Click/Hover:** - Flower center to display quantitative information.
2	The Great War (1914-2014) [26]	 War	**X**	Location	**X**	**X**	Number of deaths	**Length**: duration of war **x-position**: timeline	**X**	**Click**: flower display war information **Filter**: By location, deaths and timeline

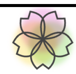
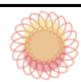
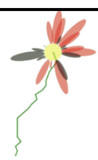
3	Cancer is not always the end [27]	 Woman	patient was symptomatic or asymptomatic	X	a petal for a decade of age	X	X	**Length**: delay in getting treatment	**Color**: how treatment affected user	X
4	Film Flower [28]	 Film	Film rating (G, PG, PG-13, R)	X	IMDB votes	Film genre	IMDB rating	X	X	X
5	Popular baby names [29]	 Baby Name (e.g., David)	X	X	Popular name	Vowels in name	X	X	X	**Filter** - by decade
6	Matches of Rugby world Cup [30]	 Match	Each ring represents match score Thickness - high score	Playing teams	X	X	X	X	**Color**: winning team	X
7	Premium League Squad 2020/21 [31]	 Match	X	Playing Teams	X	X	X	**Orientation** Team changes per match	**Color**: latest match **Size** - total team points	**Filter**: by team name, league position, and total changes
8	Investment in education in different states of the USA in 2008 [32]	 Information of investment	X	X	More investment per student	**Color hue**: the ratio of private investment	Total investment	X	X	X

Table 3.1: Summary of flower encodings in related projects

Additionally, we referred to the ranking of perceptual tasks [33] given by Jock D. Mackinlay to encode the categorical data accurately and effectively. Based on our research, the following encodings were selected for both the visualization.

- **Harasser/Victim rank: color hue**

  To represent the distinct status of the harasser/victim, five different colors were selected based on the inspiration from flowers in the real world. Color hue is a powerful visual channel to encode categorical information in terms of its effectiveness and accuracy [34].

- **Harasser gender: line pattern**

  To encode gender, we made sure to stay away from any kind of gender stereotypes in the visualizations. The line pattern of the circle outline was selected to encode the gender of the harasser.

- **Victim's field of study: shape**

  For metaphoric visualization, we choose the shape of a petal to represent the victim's various fields of study. While for the abstract visualization, we selected the shape of a polygon to represent the same. Like color, shape visual channels can distinctly represent multiple categories effectively [34].

- **Victim's expressiveness (event): size**

  The event description text data was displayed as it is in the visualization. We preserve the qualitative nature of each survey response by allowing users to read about each incident description provided by the victim. For demonstrating the victim's openness to talk about the incidents, each incident (flower/polygon enclosed in a circle) visual size was scaled in proportion to the number of words used in the event description by a victim.

- **Victim's institute type: no encoding**

  To reduce the complexity of the visualization, no visual channel was assigned to the victim's institute type. Users can have difficulties perceiving information if a visualization has too many visual encodings used simultaneously, also called conjunction [34].

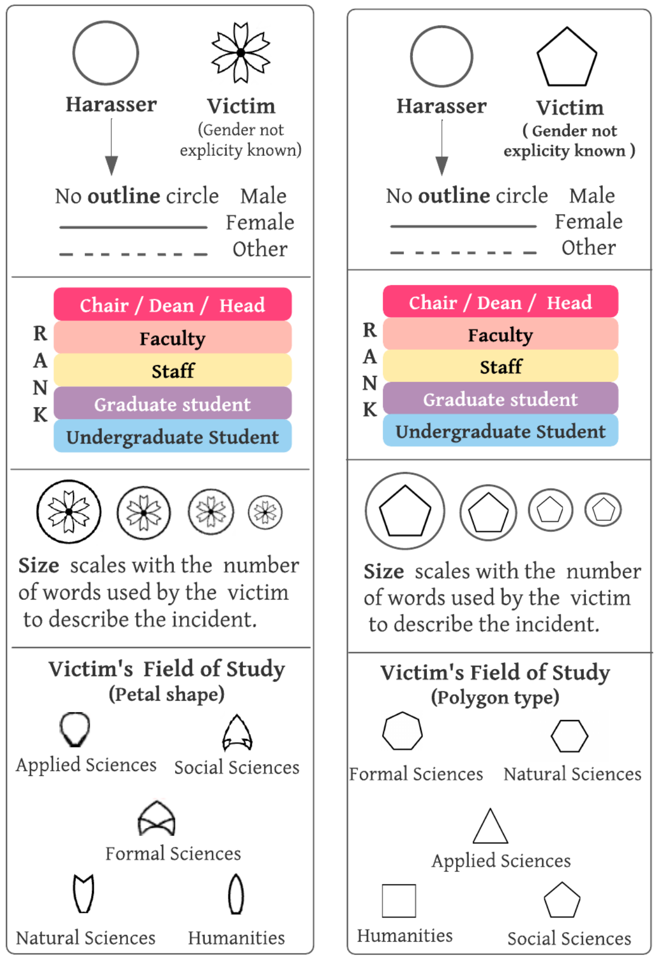


Figure 3.4: Legends of the metaphoric and the abstract visualization

3.5 Interactivity

Taking inspiration from Yi et al. [21]'s taxonomy of interaction techniques, we foster interactivity in the visualization in the following ways:

- **Abstract/Elaborate**: We provided users with an option to read the complete details of each incident by clicking on it. We believe this interactivity can help in generating stronger empathy of users towards victims and humanize the data.

- **Connect**: Users can hover over the incident visual to see all the information associated with the incident (e.g. - victim's field of study, harasser gender, etc.)

- **Filter**: Participants can group the incidents based on the victim rank, harasser rank, harasser gender, victim institute type, and victim's field of study.

By integrating the above interactivity techniques in the visualization, we aim to foster engagement and empathy by allowing users to obtain details on-demand. Hovering over an incident will provide more detailed values and grouping the data will allow users to focus more on the part of the visualization they want to invest in. By clicking on an incident, users will be able to read the complete event description as self-reported by the victim on the left panel of the visualization. We think that allowing a user to read complete event descriptions would specifically foster empathy in users.

3.6 Implementation

We implemented two different types of visualization using D3.js, JavaScript, and HTML/CSS. Considering the discussed designs and encodings, in both the visualizations, six data dimensions were illustrated, and the variable's visual encoding was kept identical. At first, we implemented flower and polygon visuals shown in figure 3.5, using the d3.js SVG path, and the cubic curve command.

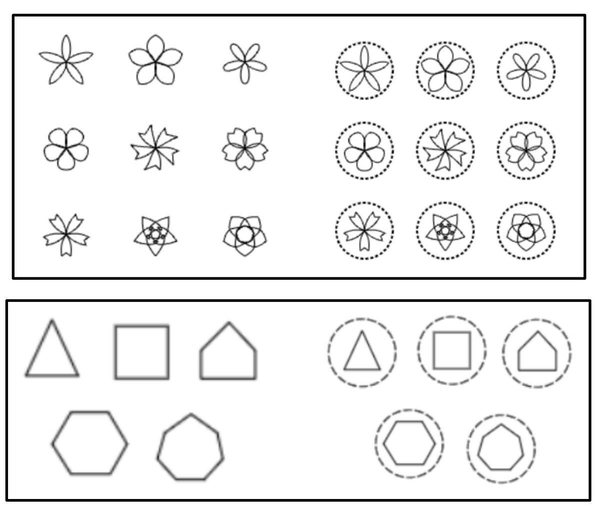


Figure 3.5: Implemented visuals of the metaphoric and the abstract visualization

Once we had built the Document Object Model (DOM), we bound the dataset with it. The next step was to implement the data-driven transformations and visual encodings in each visualization separately. The following D3.js scales were used to map a few dimensions of data with the visual representation:

- **d3.scaleOrdinal()** - Used to map victim/harasser rank categorical data type to color hue.
- **d3.scaleLinear()** - Used to map the event description quantitative aspect (number of words in event description) to the size of the incident.

To add the discussed interactive features in the visualization we took advantage of D3.js events and force layout strategy.

- **Abstract/Elaborate**: We used the click event to manage the selection and deselection of an incident. The selection of an incident by users presents the complete event description to users in the left panel of the visualization. On clicking back anywhere on the white screen near the flower, the details of the incidents disappear, and all the incidents get selected again.

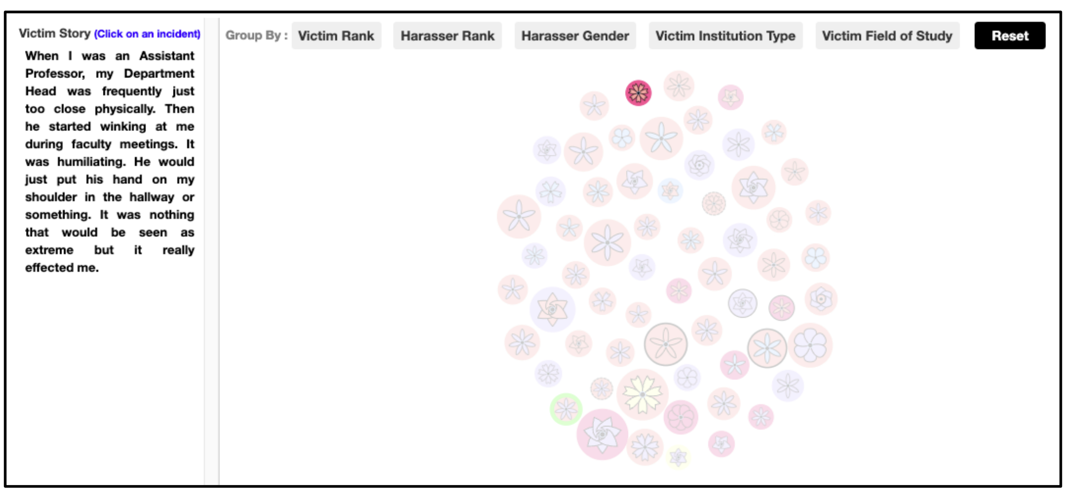


Figure 3.6: Abstract/Elaborate interactivity in the metaphoric visualization

- **Connect**: To implement the tooltip that displays additional information (e.g. - victim’s field of study, harasser gender, etc.) on hover we used the mousenter and mouseout events provided by the d3.js.

Figure 3.7: Tooltip display on incident hover in the metaphoric visualization

- **Filter**: To implement grouping of incidents based on the data dimension like victim status, harasser gender, etc. and we used the d3.js force layout. The force layout in d3.js makes it easy to position the elements in the desired manner by iteratively updating the position of elements as per the given condition. We used the forceX and forceY functions to attract the elements to respective x-coordinate and y-coordinates based on the element's category. We also used the forceCollide function to stop the elements from intersecting with each other. The grouping was triggered by clicking on the gray buttons provided at the top of the visualization.

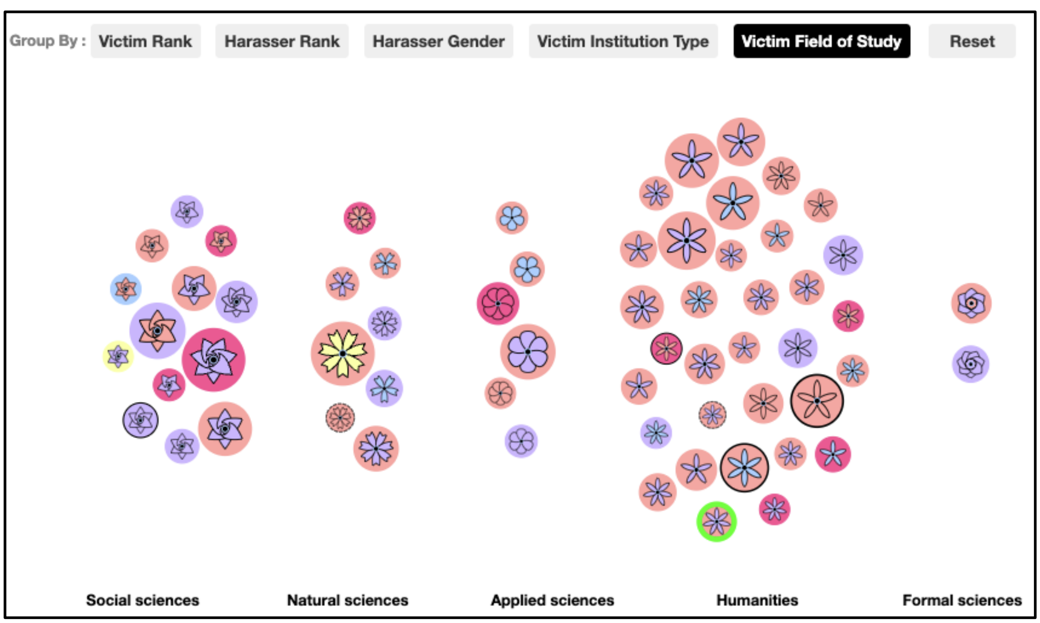


Figure 3.8: Grouping/filter interactivity in the metaphoric visualization

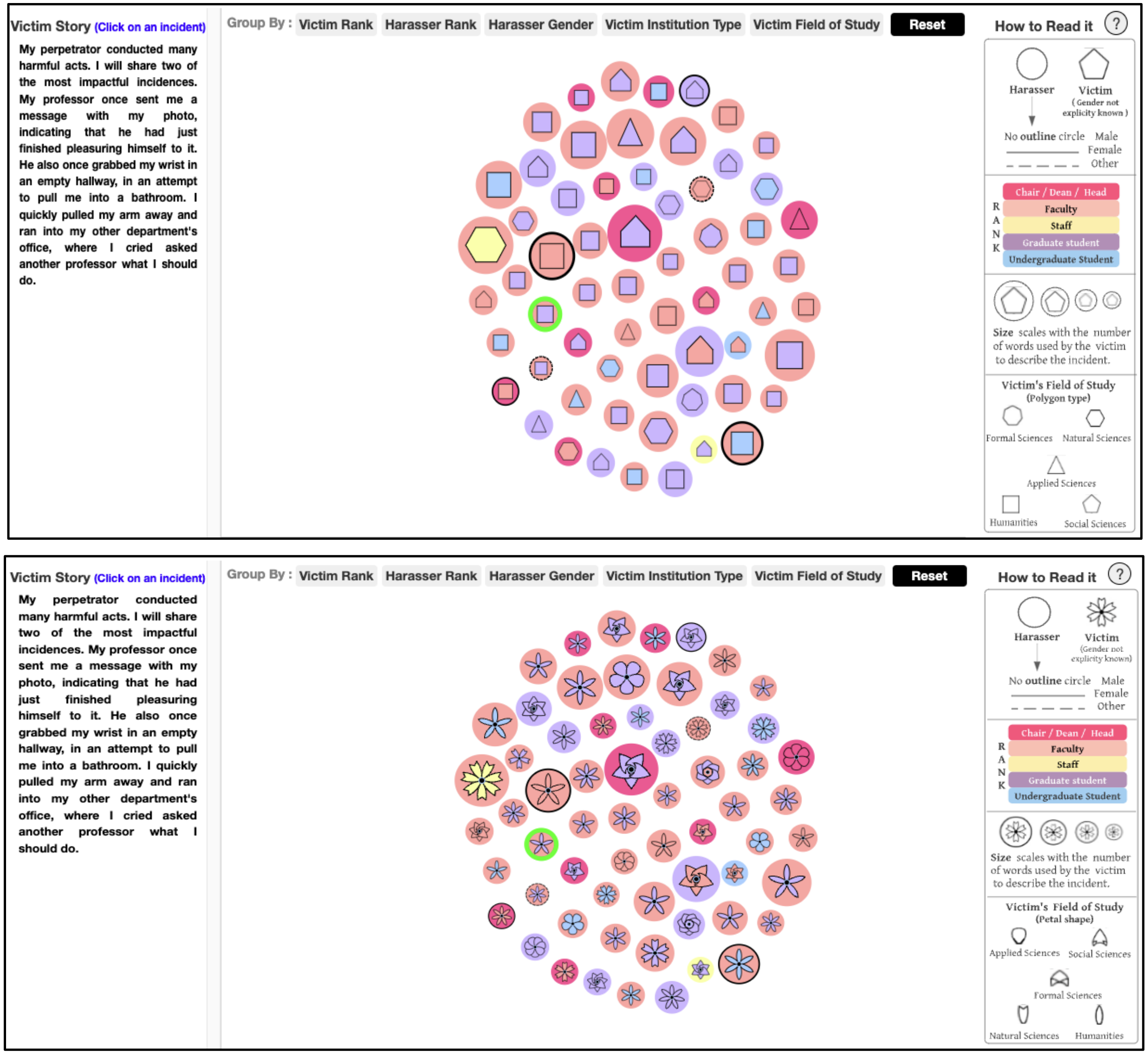


Figure 3.9: Final metaphoric and the abstract interactive visualization

Chapter 4

Experiment

4.1 Experiment Design

To evaluate whether the implemented visualizations influenced viewer empathy and engagement, we implemented a static website for conducting the experiment. The experiment design consisted of instructions, questionnaires, and visualization screens. To store the data of the questionnaires and visualization-related tasks, we connected the static websites to google spreadsheets using the google App script API. The websites were hosted on GitHub.

As can be seen in figure 4.1, the experiment design consisted of the following three parts:

Part A - This first part presents the participant with two types of forms to fill - the demographic form and the empathy questionnaire.

Part B - After completing part A and clicking on the "submit" button, a text blurb at the center of the page shows information related to the visualization they are going to see next. This information includes a brief introduction to the visualization, details of the legend, and instructions about how to interact with the visualization. Once the user closes the text blurb, either the abstract or the metaphoric visualization is presented, along with three simple, visualization-related questions that they are being asked to answer. After they have answered the questions, the participants are shown another text blurb instructing them to interact with the visualization for a few minutes and describe the interesting patterns or insights they uncovered related to the visualization.

Part C – After the participants are done interacting with the visualization, they are asked to complete an engagement questionnaire and an empathy questionnaire.

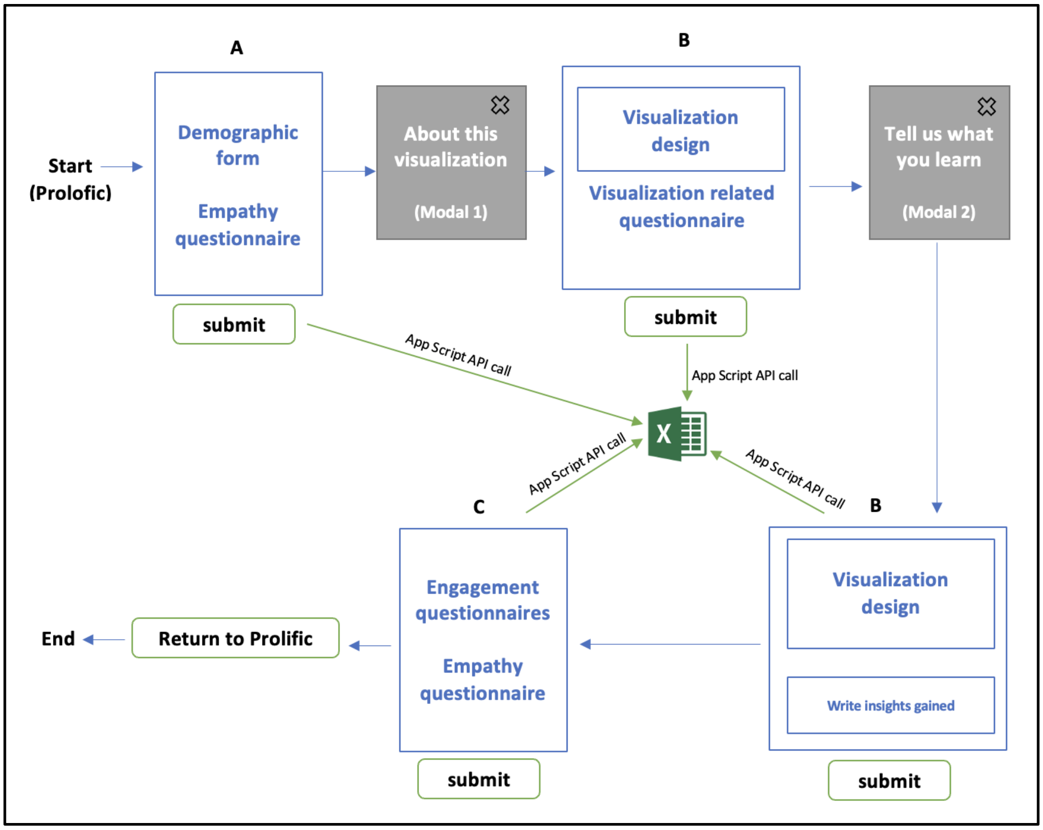
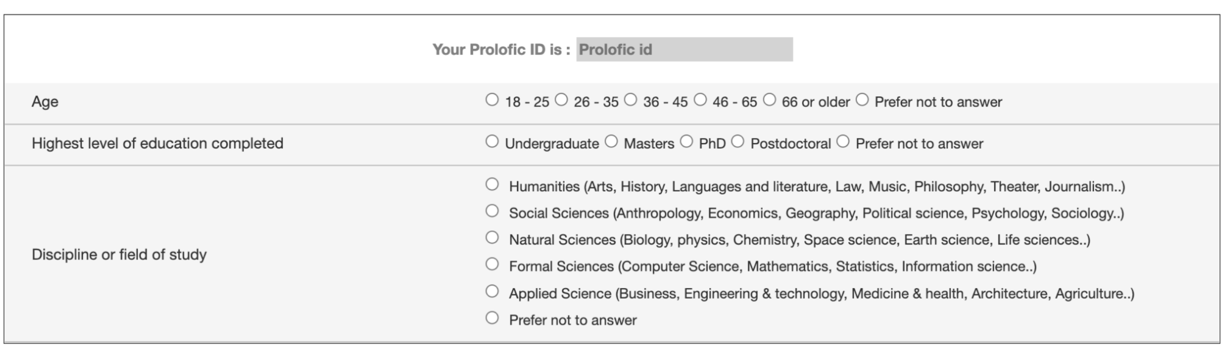


Figure 4.1: Blueprint of the experiment design

There four different questionnaires used for the experiment are as below:

1. Demographic questionnaire

Figure 4.2 shows the three demographic-related questions asked to the participants.



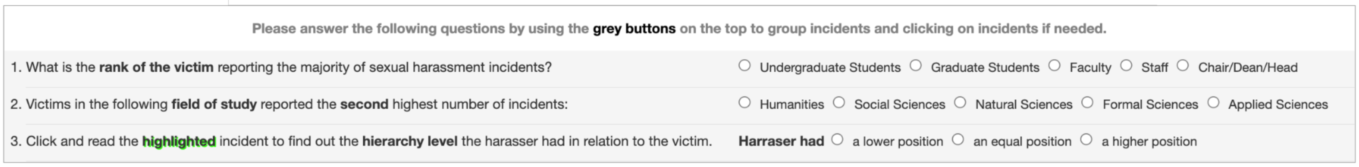
Your Prolofic ID is : Prolofic id

Age	○ 18 - 25 ○ 26 - 35 ○ 36 - 45 ○ 46 - 65 ○ 66 or older ○ Prefer not to answer
Highest level of education completed	○ Undergraduate ○ Masters ○ PhD ○ Postdoctoral ○ Prefer not to answer
Discipline or field of study	○ Humanities (Arts, History, Languages and literature, Law, Music, Philosophy, Theater, Journalism..) ○ Social Sciences (Anthropology, Economics, Geography, Political science, Psychology, Sociology..) ○ Natural Sciences (Biology, physics, Chemistry, Space science, Earth science, Life sciences..) ○ Formal Sciences (Computer Science, Mathematics, Statistics, Information science..) ○ Applied Science (Business, Engineering & technology, Medicine & health, Architecture, Agriculture..) ○ Prefer not to answer

Figure 4.2: Demographic questionnaire

2. Visualization-related questions

The participants were asked three simple visualization-related questions. The objective of the questions shown in figure 4.3 was to force the participant to interact with the visualization and get familiar with all possible interactions and legends of the visualization.



Please answer the following questions by using the **grey buttons** on the top to group incidents and clicking on incidents if needed.

1. What is the **rank of the victim** reporting the majority of sexual harassment incidents?	○ Undergraduate Students ○ Graduate Students ○ Faculty ○ Staff ○ Chair/Dean/Head
2. Victims in the following **field of study** reported the **second** highest number of incidents:	○ Humanities ○ Social Sciences ○ Natural Sciences ○ Formal Sciences ○ Applied Sciences
3. Click and read the **highlighted** incident to find out the **hierarchy level** the harasser had in relation to the victim.	**Harraser had** ○ a lower position ○ an equal position ○ a higher position

Figure 4.3: Visualization-related questionnaire

3. Empathy Questionnaire

To measure empathy, the Multidimensional Emotional Empathy Scale (MDEES) questionnaire, developed by Caruso and Mayer [19] was used in the visualizations. It is a self-reported empathy scale designed to assess emotional empathy. We chose this scale as it broadly covers both positive and negative emotional-response situations and Caruso, and Mayer reported a reliability coefficient of 0.86 with this scale. For each item, participants provide their response on a five-point Likert scale with even weighting ranging from strongly disagree (1) to strongly agree (5). Figure 4.4 illustrates the 30 questions in the MDEES questionnaire, and the highest possible empathy score is 150. Participants were asked to complete the questionnaire twice, once at the beginning of the experiment and a second time in the end after they are done interacting with the visualization. Thus, we will be able to observe a change in empathy by contrasting the responses before with the responses after a participant interacts with the visualization.

1. I feel like crying when watching a sad movie.
2. Certain pieces of music can really move me.
3. Seeing a hurt animal by the side of the road is very upsetting.
4. I don't give others feelings much thought.
5. It makes me happy when I see people being nice to each other.
6. The suffering of others deeply disturbs me.
7. I always try to tune in to the feelings of those around me.
8. I get very upset when I see a young child who is being treated meanly.
9. Too much is made of the suffering of pets or animals.
10. If someone is upset, I get upset too.
11. When I am with other people who are laughing, I join in.
12. It makes me mad to see someone treated unjustly.
13. I rarely notice when people treat each other warmly.
14. I feel happy when I see people laughing and enjoying themselves.
15. It is easy for me to get carried away by other people's emotions.
16. My feelings are mine alone and are not a reflection of how others feel.
17. If a crowd gets excited about something, so do I.
18. I feel good when I help someone out or do something nice for someone.
19. The feelings I feel for others are deep.
20. I don't cry easily.
21. I feel other people's pain.
22. Seeing other people smile makes me smile.
23. Being around happy people makes me feel happy too.
24. TV or news stories about injured or sick children greatly upset me.
25. I cry at sad parts of the books I read.
26. Being around people who are depressed brings my mood down.
27. I find it annoying when people cry in public.
28. It hurts to see another person in pain.
29. I get a warm feeling for someone if I see them helping another person.
30. I feel other people's joy.

Figure 4.4: Empathy questionnaire

4. Engagement Questionnaire

As part of assessing user engagement, we collected their behavioral indicators as well used a self-reporting engagement questionnaire. We used an engagement Questionnaire called

VisEngage presented by Y. Hung and P. Parsons [24] to measure user engagement. VisEngage has a total of 22 questions, two questions from distinct engagement characteristics. This makes VisEngage more concrete than the abstract characteristics of a self-assessment questionnaire. To have uniformity among the questionnaires used in the experiment, we transformed the original seven-point Likert scale of the questionnaire to a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5) with even weighting. Participants were asked to fill out the engagement questionnaire immediately after interacting with the visualization. As seen in figure 4.5, there are 22 questions in the empathy questionnaire, so the highest possible engagement score is 120.

1. While using this interactive visualization, I found its look and feel to be pleasing.
2. The layout of this interactive visualization is clear and balanced.
3. While using this interactive visualization, I felt absorbed to the extent that I was not aware of my surroundings.
4. While using this interactive visualization, time seemed to pass quickly.
5. While using this interactive visualization, I enjoyed and accepted any challenges it presented.
6. While using this interactive visualization, I had to think carefully, deeply, or reflectively.
7. While using this interactive visualization, its functions and features worked as I expected.
8. While using this interactive visualization, I felt in control.
9. While using this interactive visualization, I learned something that I had not known before (a piece of information).
10. While using this interactive visualization, I learned and figured out how to use it along the way.
11. While using this interactive visualization, I felt as though I was moving in or through it to learn about its content or message.
12. While using this interactive visualization, I was exploring its features and content in a gradual fashion.
13. While using this interactive visualization, I found myself imagining things not directly related to what I was seeing in the visualization.
14. While using this interactive visualization, I found myself generating new and original thoughts or ideas.
15. While using this interactive visualization, I found myself concentrating on specific aspects or features of the visualization.
16. While using this interactive visualization, I had to pay attention to multiple things at the same time.
17. The content or message of this interactive visualization was interesting to me.
18. The features or interactions provided in this interactive visualization were interesting to me.
19. The look and feel of this interactive visualization were novel and fresh.
20. The features or interactions provided in this interactive visualization were novel and fresh.
21. While using this interactive visualization, I experienced a deeper understanding of the topic.
22. I would want to use this interactive visualization if I saw it somewhere else and was not required or encouraged to use it.

Figure 4.5: Engagement questionnaire

To strengthen the evaluation of engagement, we also collected the following behavioral indicators of the participants:

1. The number of times the participant clicked on each grouping option.
2. The total number of incidents the participant clicked on.
3. The exact incidents that were clicked on by the participants.
4. The total time spent by the participant for each part of the experiment.

4.2 Pilot Study

Before launching the main study, eight pilot studies were conducted to test and improve the experiment environment. Figure 4.6 shows the iterative process of pilot runs and improvements associated with each trial.

Participant comment/question/action/feedback **Improvements**

Pilot - 1 (Video Call)

Selecting answers by clicking on the text will be helpful when filling out multiple-choice questions in the forms.	Made form text clickable. To select an answer in the forms, users can click on the radio button or text.
It will be good to see more quantitative information by hovering over an incident.	Added tooltip to read quantitative information of the victim's testimony on hovering over an incident.
Participants confirmed the meaning of the academic discipline and asked how the chair is different from the faculty.	Renamed academic Discipline to the field of study (layman's term). Added more information in the "About this visualization" modal to explain how faculty is different from the Chair.
Participant confirmed the meaning of the following statements: 1. Too much is made of the suffering of pets or animals. 2. My feelings are my own and don't reflect how others feel. 3. feel deeply for others.	Rephrased the statements in the empathy form. 1. The suffering of animals or pets is over-emphasized. 2. My feelings are mine alone and are not a reflection of how others feel. 3. The feelings I feel for others are deep.
Participant spent time exploring the visualization but was not writing the insights as instructed in the study.	Updated the visualization instructions to encourage users for side-by-side writing along with exploration.
Participant asked if the empathy form was repeated by mistake.	To clarify, added a comment to refill the empathy form again.

Pilot - 2 (Video Call)

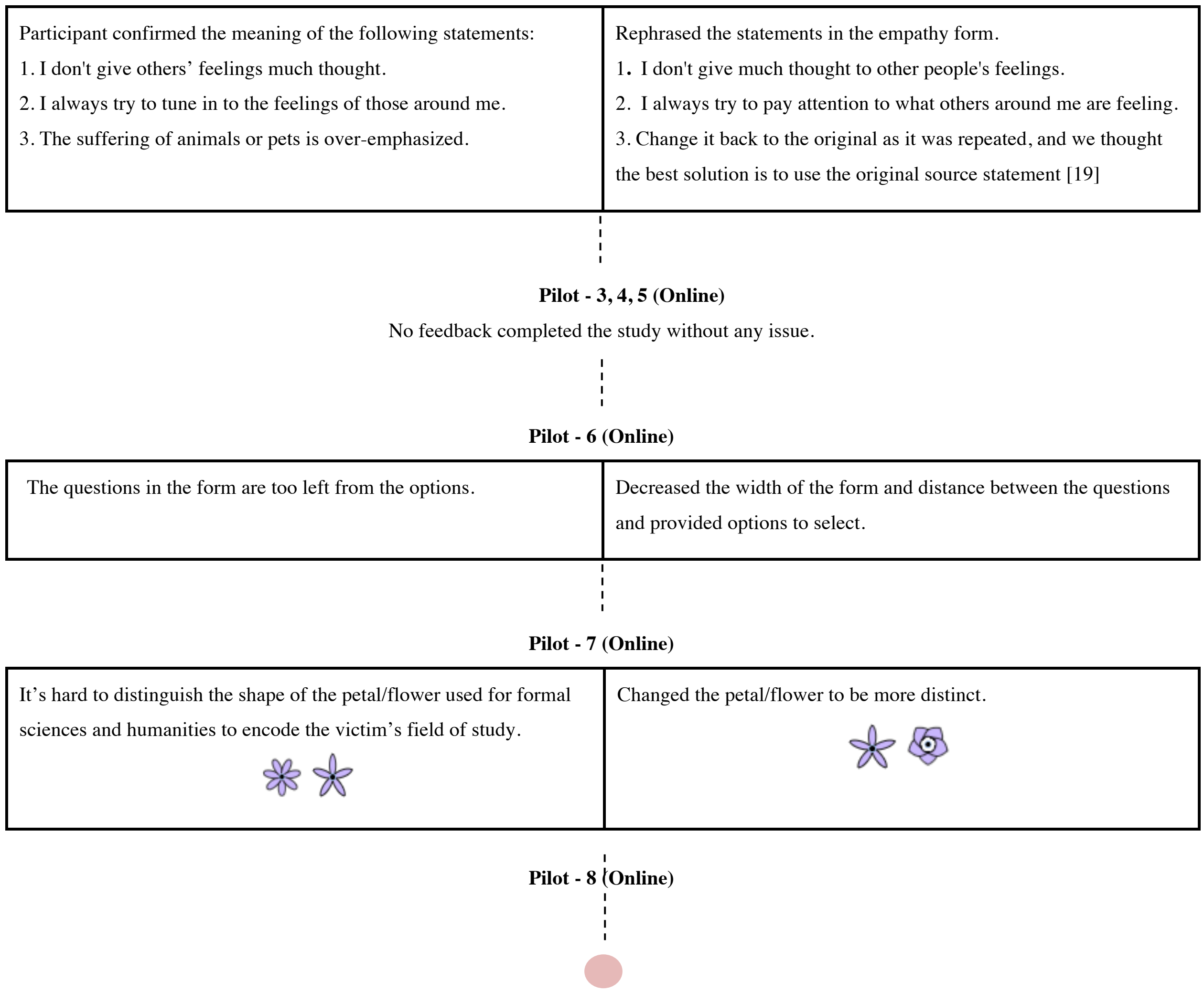


Figure 4.6: Pilot studies feedback and improvements

4.3 Main study

The main experiment was conducted online using the service at https://www.prolific.co/ (prolific). The recruitment and screening of the participants were handled by the prolific platform. A total of 60 people were randomly selected from Canada, UK, US and were pre-screened according to the criteria listed in the prolific platform:

- Age: 18 years or older

- Highest Level of Education: Technical/community college, Undergraduate degree (BA/BSc/other), Graduate degree (MA/MSc/MPhil/other), Doctorate degree (Ph.D./other) The pool consists of more than 170 million unique members.
- Gender identity: Male or Female or Other (Trans Male/Trans Man, Trans Female/Trans Woman, Genderqueer/Gender Non-Conforming, Different Identity).

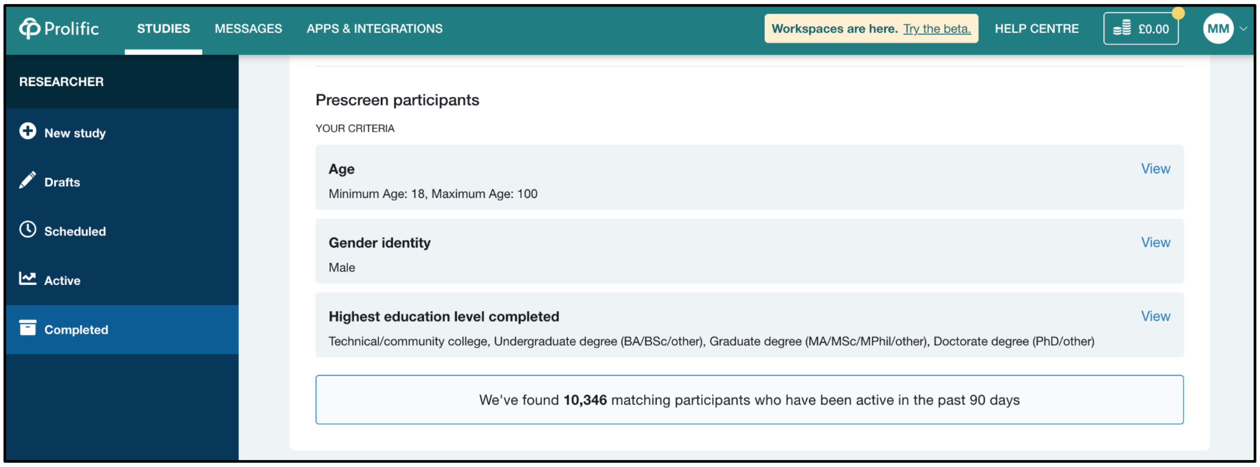


Figure 4.7: Pre-screening filters on the prolific platform

As shown in figure 4.7, we did not explicitly ask participants for their gender identity, it is a part of the eligibility criteria handled by the prolific platform. The complete experiment was divided into six conditions, that we translated into six prolific studies according to the visualization type and gender identity. Two visualization types (metaphoric and abstract) and three gender identities (male, female and other) resulted in the six conditions presented in Table 4.1.

	Study Internal name	**Gender Identity**	**Participant Count**
1)	Metaphoric Visualization	Male	10
2)	Abstract Visualization	Male	10
3)	Metaphoric Visualization	Female	10
4)	Abstract Visualization	Female	10
5)	Metaphoric Visualization	Other	10
6)	Abstract Visualization	Other	10

Table 4.1: Different conditions in the experiment

The duration of each study was 20 minutes, decided based on the average result of the time taken by the participants in the prior eight pilot studies.

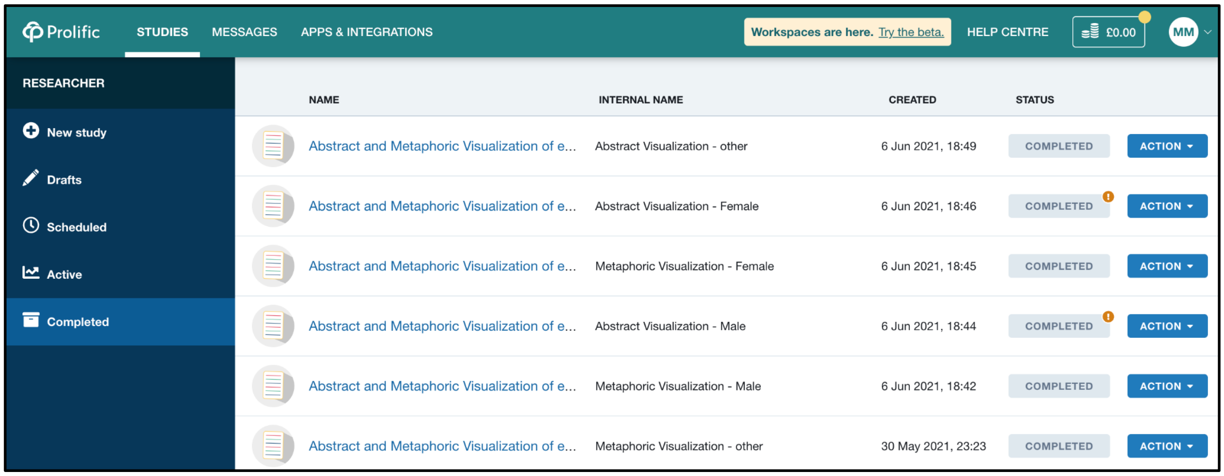


Figure 4.8: Completed conditions on the Prolific platform

We discarded a few participants based on the following criteria:

- If the participant did not complete all parts of the experiment.
- If the participant filled the empathy and engagement forms within 30 seconds.
- If a participant spent less than 60 seconds on the visualization, had no interactions, or provided some non-concrete or irrelevant insights like "this is nice" (because participants were instructed to spend a few minutes and write down the interesting pattern they discover while interacting with the visualization.).

Depending on the number of rejected participants, new participants were recruited for each condition. We reopened particular conditions to fill the space of the rejected participants. These overheads were easy to manage using the prolific platform.

Chapter 5

Results and Discussion

5.1 Results and Analysis

After completing the experiments on the prolific platform, we compared the differences between the results for the metaphoric and the abstract visualization. This chapter provides details of our analysis to understand whether metaphoric visualization elicits more empathy and engagement, as we had hypothesized.

We summarized the data of each condition by using the median as the central measure of tendency. We chose the median over the mean for the initial aggregation of results as the skewed data and outliers have a smaller effect on the median. We also summarized the data of the six conditions based on visualization type and gender identity. Given the relatively small sample size for the experiment, we rely on descriptive statistics to discuss our results instead of conducting statistical analyses. This means that these results must be read as indications that will allow us to formulate new hypotheses to test further in studies with higher statistical power.

experiment_name	pre_emp	post_emp	emp_diff	eng_score	group_clicked	incident_clicked	total_clicks	insight_features	insights_words	total_viz_time
Metaphoric_male	101	100	-1	80	8	16	24	3	35	8.18
Metaphoric_female	113	111	-2	87	7	20	27	4	40	9.57
Metaphoric_other	106	104	-2	83	9	13	22	3	71	13.30
Abstract_male	100	103	3	85	7	13	20	2	34	9.68
Abstract_female	108	106	-2	82	9	20	29	3	49	11.81
Abstract_other	104	103	-1	79	9	18	27	4	57	9.61

experiment_name	pre_emp	post_emp	emp_diff	eng_score	group_clicked	incident_clicked	total_clicks	insight_features	insights_words	total_viz_time
Metaphoric_combined	107	105	-2	83	8	16	24	3	49	10.35
Abstract_combined	104	104	0	82	9	17	25	3	47	10.36

Gender_identity	pre_emp	post_emp	emp_diff	eng_score	group_clicked	incident_clicked	total_clicks	insight_features	insights_words	total_viz_time
Male	101	102	1	83	8	15	22	3	35	8.93
Female	111	109	-2	85	8	20	28	4	45	10.69
Other	105	104	-1	81	9	16	25	4	64	11.45

Figure 5.1: Aggregated summary of the individual condition and different combinations of conditions

We concluded our findings using the data presented in figure 5.1 as below:

- **Visualization processing time:** The metaphoric groups spent (10.35) minutes on average on the visualization, while the abstract group spent (10.36) minutes. Therefore, the difference in the time taken by each group to do the study seems like not an important factor. This insight denies the assumption that the users are inclined to spend more time with metaphoric visuals which connect with the existing images in their brain's mental model.

- **Empathy analysis**: We calculated the median of the difference between participants' pre-empathy and post-empathy scores for each condition to determine whether the visualization has had any effect. The aggregated average empathy score of all 6 conditions was (105) out of (150). The metaphoric group's combined empathy difference was -2 (we found that on the average metaphoric group had a pre-empathy score of 107 and a post-empathy score of 105). While the combined empathy difference was 0 for the abstract group (we found that on the average abstract group had an equal pre-empathy score and post empathy score of 104). Therefore, the difference in the empathy of each group after interacting with the visualization is almost negligible.

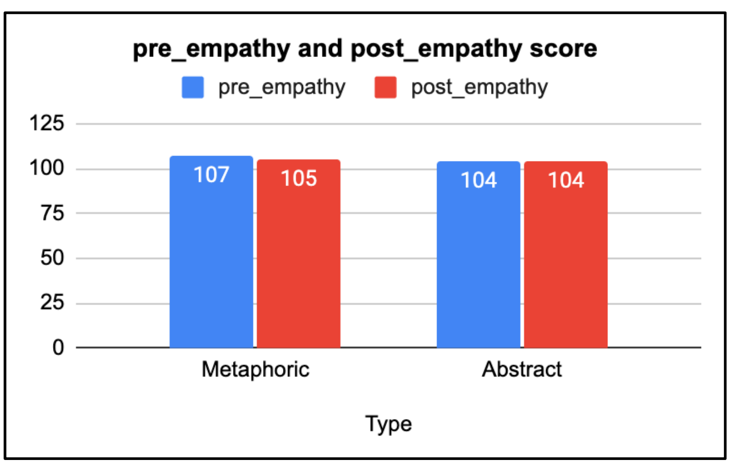


Figure 5.2: Aggregated pre-empathy and post-empathy score of metaphoric and abstract groups

- **Engagement analysis:** The average engagement score for all the 6 conditions was 83 out of 120. We did not find any significant difference in participant engagement scores and behavioral indicators (number of clicks on grouping options and incidents) between the metaphoric and abstract groups. As seen in figure 5.3, the metaphoric group had an average engagement score of 83 while the abstract group had an engagement score of 82. In terms of the behaviour indicators, metaphoric group had 24 clicks in general while the abstract group had an average of 25 clicks.

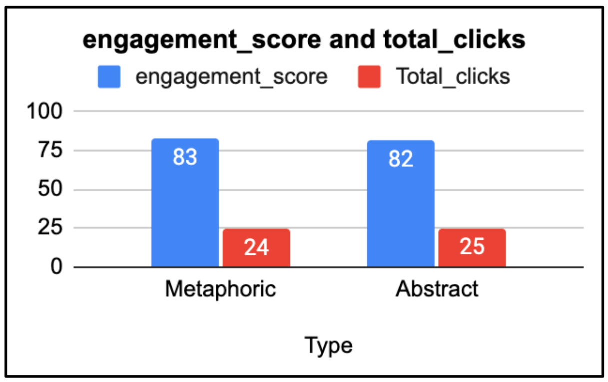


Figure 5.3: Aggregated engagement score and total clicks of metaphoric and abstract groups

- **Qualitative data analysis:** We analyzed the visualization insights provided by the participants after interacting with it as part of the experiment. The participant received a total of five points if provided insights covering all the grouping dimensions of the visualization: victim rank, harasser rank, harasser gender, victim's institute type, and victim's field of study. We found out that both the metaphoric and abstract groups provided at least 3 insights on an average. It was interesting to notice that the least mentioned insight was the victim’s institute type. A possible explanation of this finding could be as there was no visual encoding associated with this data dimension, participants may have perceived it less.

5.2 Discussion

Although our experiment differs from some of the popular prior studies [10, 11] in terms of the visual marks and empathy testing technique, we also did not find any clear change in the user’s empathy level in our study. We used a metaphoric visual and empathy questionnaire whereas the prior experiment [10, 11] used anthropographics (human-like images) and the maximum donation likelihood empathy measurement technique. Additionally, we observed slightly higher engagement and engagement in the conditions with female participants.

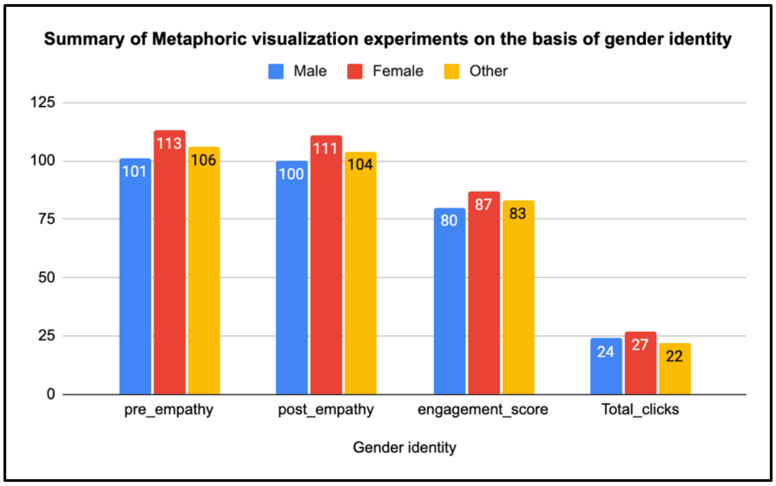


Figure 5.4: Aggregated results of metaphoric visualization based on gender identity

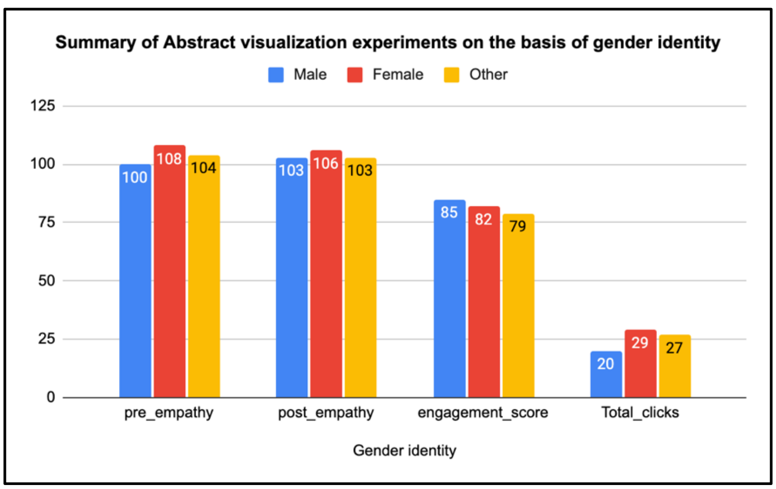


Figure 5.5: Aggregated results of abstract visualization based on gender identity

It can be seen in figure 5.4 and figure 5.5, that both the metaphoric and abstract visualization conditions with the female group had slightly higher empathy and engagement scores compared to the conditions with male and other gender identity. It is unclear whether these are real insights or noise originating from the smaller sample size of participants. Certain assumptions can be made behind this finding like our experiment, in general, caught the attention of the more empathetic females. Our study calls a need for a larger-scale study to confirm such interesting findings and to reject or accept the hypotheses for our study. We also found that measuring empathy efficiently in data visualization is a difficult task. The technique used in our study to calculate the pre and post empathy score difference to measure empathy did not seem to provide much value in the study. There is a need for more sophisticated techniques to measure empathy in the visualization world.

Chapter 6

Conclusion and Future work

6.1 Conclusion

In this project we implemented a creative metaphoric visualization for emotionally sensitive data and conducted a series of crowdsourcing studies, to compare the metaphoric visualization against a similar abstract visualization. The main difference in both the visualizations was in the terms of the visual mark. Metaphoric visualization used a flower visual symbolizing beauty, life, and fragility while abstract visualization used a polygon as the visual mark with no associated meaning. In this project, we tried to investigate the growing assumption that creative metaphoric visualization could possibly evoke more empathy and engagement in users. We assumed that the human existing mental images of flowers and their understanding could force the users to connect more with the victim. Contrary to our H1, H2 hypothesis and assumptions, our results of the crowdsourcing studies showed that both metaphoric and abstract visualization had a similar effect on participants in terms of user empathy and engagement. However, due to the small size of our study, which included only 60 participants, the reliability of these insights is quite low. A larger study is required to confirm the findings of our study. We believe that our result can serve as a basis for future studies to confirm whether metaphoric visuals are better than abstract ones for emotionally sensitive datasets.

6.2 Future Work

In terms of future work, we suggest performing the same or similar experiments with more participants for the higher reliability of the results. The participants in our experiment were randomly recruited online using the prolific platform, it will also be beneficial to perform the experiment with expert users, who are experienced, skilled, and do not have any monetary motivation. In terms of improving the visualization design space, we suggest that more realism can be incorporated into the flower. Evaluating empathy and engagement is also a complex task. In addition to the empathy questionnaire, it will be more effective to use some other method to measure empathy. More experiments using a different kind of metaphors against abstract visualization are needed to testify and consolidate whether metaphoric visualization evokes more empathy and engagement in users.

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