Investigating the Resiliency of the Framing Effect in Information Visualization

Alexandra Maroco, Daniel Gonçalves, Sandra Gama
INESC-ID, IST,
University of Lisbon, Portugal
{alexandra.maroco,daniel.j.goncalves,sandra.gama}@tecnico.ulisboa.pt

Tomás Alves
BRU-Iscte,
ISCTE – University Institute of Lisbon, Portugal
tomas.alves@iscte-iul.pt

***Abstract*—When individuals conduct complex cognitive thinking under uncertainty, their judgments and decisions may rely on individual unconscious approximations and rules of thumb. These may lead to systematic deviations from rational thinking called cognitive biases. Recent research in the information visualization field has tackled how these rationale limitations affect visualization-supported decision-making. However, there is such a small body of evidence that it offers little guidance to practitioners. The present study explores the framing effect in an information visualization context by depicting a decision-making problem regarding a hypothetical disease with visual encodings. We conducted user tests (N=91) where we collected user interaction metrics and the decision-making process between a set of options under different framing contexts. Our findings suggest that bar charts with error bars help mitigate the framing effect for most of the experiment sample. Developing cognitive bias-aware decision support systems is of utmost importance to leverage the full potential of information visualization and make it widely available to jobs where visualization-supported decisions are critical.**

***Index Terms*—Framing Effect, Cognitive Bias, Information Visualization, Uncertainty**

I. Introduction

Despite striving to do so, humans have too limited cognitive abilities and are, thus, unable to truly make rational decisions [1]. Consequently, humankind is forced to rely on heuristics. A *heuristic* consists of a mental strategy our brain forms to simplify all the information around us, where merely the parts each deems relevant to the situation/decision at hand are considered. These allow individuals to solve problems and make judgments quickly and effectively, reducing the mental effort of such actions. While aiding us, said heuristics also lead to systematic deviations from rationality in judgment, designated by Tversky and Kahneman [2] and Kahneman et al. [3] as *cognitive biases*. These deviations manifest in distinct ways, which led to several studies proving the existence of a wide variety of cognitive biases [4].

There has been a growing interest both in cognitive biases [5], [6] and decision-making [7], [8] within the information visualization (InfoVis) community. Notwithstanding, the intersection between said fields remains predominantly unexplored, and very few researchers explore a particular cognitive bias within the visualization context [4]. Among the cognitive biases that show a potential transfer of the priming effect to an InfoVis context, we decided to focus on the *framing effect*. The **framing bias** is a cognitive bias where there is a variation of outcomes in the decision-making process due to how information is presented, i.e., when the *framing* of said information causes a deviation from a rational choice. In particular, the reference point used to evaluate the consequences of a decision is the critical element of *framing* [9], [10]. Accordingly, modifications to the reference point of the framing can have a significant impact on the way a subject makes a decision [11]. For instance, Kong et al. [12] showed that the slant of the title influenced the perceived main message of a visualization.

Researchers usually apply two frames, each with a distinct valence. A particular example of this bias is known as the *loss aversion* [13] where alternatives are gains or losses. In a *positive frame*, the information is framed as a gain, and people tend to avoid risks. In contrast, it is presented as a loss in a *negative frame*, leading individuals to seek risk. Research in InfoVis has already shown its effect in decision-making [14], [15]. For instance, Zhang et al. [15] focused on this case by showing that startup companies with static tabular star ratings visualizations tended to be subject to lose aversion behaviors. However, there seems to be little work done, as evidenced by Dimara et al. [4] when classifying this bias as "discussed in visualization research as important, but not yet studied".

Inspired by these findings, our study aims to explore the effect of framing bias in information visualization. We focus on simulating the original decision problem by Tversky and Kahneman [10] using two bar chart visualizations - one for each framing type mentioned. In particular, we represent the risk in the framing through uncertainty with error bars. Therefore, we try to answer the following research question: *Can bar charts with error bars alleviate the framing effect?* We conducted user tests ($N = 91$) to understand whether the framing affected the decision-making based on user interaction and reported choices. Our preliminary results suggest that visualization, mainly using error bars in bar charts, may help individuals be less susceptible to the framing effect. Our contributions provide further understanding to future studies that leverage cognitive bias-aware mechanisms to promote more rational decision-making.

II. Related Work

Recent research in the information visualization field has tackled how cognitive biases affect decision-making [4], [16]–[18]. Nevertheless, this research field has struggled to find evidence in the intersection of Psychology, Decision Systems, Intelligence Analysis, and Visualization research to create a solid taxonomy of cognitive biases. In particular, while most taxonomies organize biases according to why they occur based on cognitive mechanisms and explanatory theories, Dimara et al. [4] leverage task types to create the most extensive taxonomy in the literature that includes biases studied in the different mentioned research domains.

Dimara et al. [4] categorize 154 cognitive biases with seven main categories: estimation, decision, hypothesis assessment, causal attribution, recall, opinion reporting, and others. In particular, the authors classified the framing effect in the decision category. Decision tasks include selecting one over several alternative options. One instance already studied in InfoVis is the *attraction effect* – choices affected by irrelevant dominated alternatives [19]. It is also the only cognitive bias with evidence for its alleviation [20]. In particular, Dimara et al. [20] mitigated the attraction effect by allowing users to remove information from scatterplots that should not affect rational decision-making.

Research has consistently shown that the framing effect (choices affected by whether alternatives are presented with positive or negative connotations [10]) is one of the most prominent biases in decision-making [21]. The closest works examine a particular case of framing effect known as *loss aversion* – choices framed as a gain or a loss. For instance, while Zhang et al. [15] found evidence of this bias when startup companies presented with static tabular visualizations of star ratings, Dasgupta et al. [14] reported evidence of loss aversion as a leading cause of problems in maps and line charts. Moreover, Bedek et al. [22] proposed theory-driven approaches for cognitive bias detection and mitigation. Specifically for the framing effect, the authors highlight how the aspect ratio of visualization and the ordinate starting at numbers different from 0 in bar charts may affect user perception. However, we found no work focused on the relationship between information visualization and framing bias besides being discussed as relevant in visualization research [23], [24].

There is already a body of research with evidence for the presence of cognitive biases in InfoVis by exposing participants to a text narrative before seeing a visualization [25], or varying the position of data instances [26], uncertainty encoding [27], scale proportions [28], and color scheme [29]. More recently, Alieva [30] highlighted the importance of considering cognitive biases in data visualizations by showcasing the potential increase in political polarization and skepticism. We can leverage this knowledge to explore which visualization techniques prime individuals based on the utility theory and devise a set of design guidelines to improve the design of visualization-based decision support systems.

III. Methodology

This section starts by detailing the techniques used to trigger the framing effect. We then describe the procedure and data analysis procedures employed in the study.

A. Framing Strategy

A rational choice requires that the preference between options should not alter nor reverse with changes in frame. Caused by the limitations of humankind's cognitive abilities, however, Tversky and Kahneman [10] observed systematic reversals of preference by variations in the framing of acts, contingencies, or outcomes. Framing refers to the process of decision-making, highly correlated with the subject's "conception of the acts, outcomes, and contingencies associated with a particular choice" [10].

Tversky and Kahneman [10] applied a brief questionnaire to individuals asking them to choose between two alternative treatment programs to act upon a hypothetical Asian disease expected to affect 600 people. Two different problems were presented, each framed differently. *Problem 1* presented the consequences of its two programs through a *positive* frame, whereas *Problem 2* stated its outcomes with a *negative* frame (see Table I). Problems were identical in terms of the consequences (programs *A* and *C*, and programs *B* and *D*), the only difference being the framing variations of the outcomes of each program. Yet, a majority of participants chose program *A* over *B* (72% versus 28%), while in *Problem 2*, the majority chose program *D* over *C* (78% versus 22%). In particular, Tversky and Kahneman [10] concluded that decisions taken upon a ***positive*** frame tend to be **risk-averse**. In contrast, a problem presented through a ***negative*** frame favors **risk-taking** behavior. Therefore, Tversky and Kahneman [10] concluded that changes to the reference point of the framing can have a significant impact on the way a subject decides.

For our study, we opted to pose the same decision-making problem from their research - a hypothetical disease expected to affect 600 people - with minor adaptations (see Table II). We employ the same two framing conditions in our work - *positive* and *negative*. Additionally, each study condition has two options: a *not risky* choice - options *A* or *C* - and a *risky* one - options *B* or *D*.

To the best of our knowledge, there is an absence of a validated apparatus to evaluate the framing bias, i.e., a measure to determine whether an individual has been subject to it. Considering this, we needed to define how we categorized an individual as *primed*. Based on the utility theory [31], [32], we are fixing the expected value of each option within a frame condition as the same - 200 survivors for the *positive* condition and 400 deaths for the *negative* one. Leveraging this approach means there is no optimal decision since both are expected to provide the same outcome value. Therefore, the decision-maker solely has to decide whether they follow a risk-averse (options *A* and *C*) or a risk-taking (options *B* and *D*) strategy.

To identify whether a participant was primed in the individual evaluation, we assume we primed them if they changed their decision between frames. For instance, we assume that

TABLE I
ORIGINAL PROBLEM FROM TVERSKY AND KAHNEMAN [10].

Program	*Framing*	*Options*	
Problem 1	Positive	Not risky	A: If adopted, 200 people will be saved.
		Risky	B: If adopted, there is 1/3 probability that 600 people will be saved, and 2/3 possibility that no people will be saved.
Problem 2	Negative	Not risky	C: If adopted, 400 people will die.
		Risky	*D*: If adopted, there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die.

TABLE II
FRAMING CONDITIONS AND RESPECTIVE OPTIONS.

Program	*Framing*	*Options*	
Problem 1	Positive	Not risky	A: If adopted, 200 people will be saved.
		Risky	B: If adopted, 150 to 250 people will be saved.
Problem 2	Negative	Not risky	C: If adopted, 400 people will die.
		Risky	D: If adopted, 350 to 450 people will die.

the frame primed the individual if the participant chose the *risky* option in the negative framing and the *not risky* choice in the positive framing.

B. Visualizations

As for the chart type to represent the setting of our study, we based our decision on the work of Bancilhon et al. [33]. We opt to leverage a bar chart to understand the impact of visualization in decision-making. In particular, Bancilhon et al. [33] showed that depicting the possible choices through bar encodings was the approach that exhibited behavior that was most similar to showing the information solely through text. Therefore, we decided to use bar charts to represent the programs of our study. Past research recommends presenting uncertainty information alongside point estimates, for example, by showing intervals in which estimates could fall [34], [35]. Regarding the risk factor of the choices, i.e., whether it is risky or not risky, we leverage error bars to represent the uncertainty of outcomes (present both in option *B* and *D*). The two conditions of our study are represented in Figures 1 and 2.

Each participant in our research was exposed to framing conditions - *positive* and *negative*. Kwak and Huettel [36] discovered that the sequential positioning of visual information processing may change the impact the information shown has on the participants and, therefore, bias their choices. In light of these findings, the order in which individuals underwent each condition was arbitrary - starting with either the *positive* or *negative* one and then going through the other one. Additionally, for each condition, the position of the risky (*B* and *D*) and not risky (*A* and *C*) options were displayed randomly on either the left or right side of the visualization. These research details, likewise, aid us in preventing potential biasing.

C. Measures

We leverage user interaction, self-assessment, and personality metrics to have a better understanding of how the framing context affects the decision-making process:

User interaction Past work by Wall et al. [5] recommend recording mouse activity to understand how participants interacted with the visualization. We decided to record the **interaction volume**, which is the number of hovers per program (bar) each participant triggered while taking their choice for each framing condition. When hovering over each program, the tester has access to the exact values of the hovered program (Figure 2, on the right-hand side). For instance, if the user hovers over option C, the exact value 400 is added with a tooltip to the bar. If the hovered option is a *risky* one, such as option D, the tooltip provides the upper and lower bounds of the confidence interval. Additionally, we collect the **decision time** in seconds. We start counting after the assistant explains the procedure to the tester and end when the participant submits their decision.

Decision-Making Per framing context, we record the **choice** of each participant (*risky* or *not risky*). Additionally, we collect the **perceived risk of the choice taken** since subjective feedback has provided further insights into the decision process [37], [38]. In particular, participants have to assess per framing context the riskiness of their choice through a seven-point Likert scale ranging from *Not risky at all* (1) to *Extremely risky* (7).

Demographics We recorded the gender, age, and self-reported visual acuity of each participant and whether they were color-blind. Moreover, we collected participants' subjective overall risk attitude and familiarity with each idiom chosen for our research.

D. Expected Findings

Our study design is based on the work of Tversky and Kahneman [10]. We aim to understand whether visualization can attenuate the priming effect by answering the following research question: *Can bar charts with error bars alleviate the framing effect?* In case visualization does not promote resiliency to the framing effect, decisions taken upon our *positive* framing condition will be risk-averse (option A) and risk-seeking (option D) for the negative one. However, we cannot make robust predictions regarding the framing effect since there is no other study on this topic. Concerning decision time, we anticipate participants will take longer to decide on the *negative* framing condition of the study as opposed to the *positive* one, given the nature of the frame. Accordingly, we expect them to assign a lower risk score for the choice in the positive framing condition. Further, we presume the *negative* framing condition will require more hovers than the *positive* one. Moreover, per framing condition and due to the risk these options entail, we predict the *risky* options (B and D) to detail a higher number of hovers than the *not risky* ones (A and C).

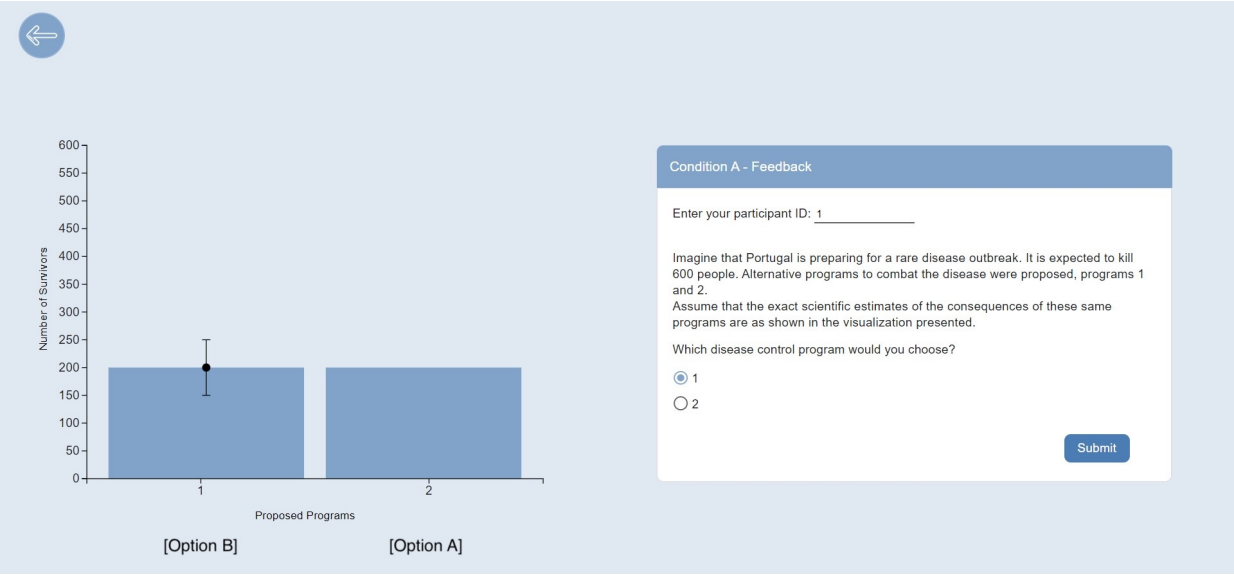


Fig. 1. The ***positive*** framing condition of the study, indicating the survivors for each option. Participant's ID and choice selected, thus, showing the submit button. The specific options are annotated between square brackets on the image and were not shown to participants.

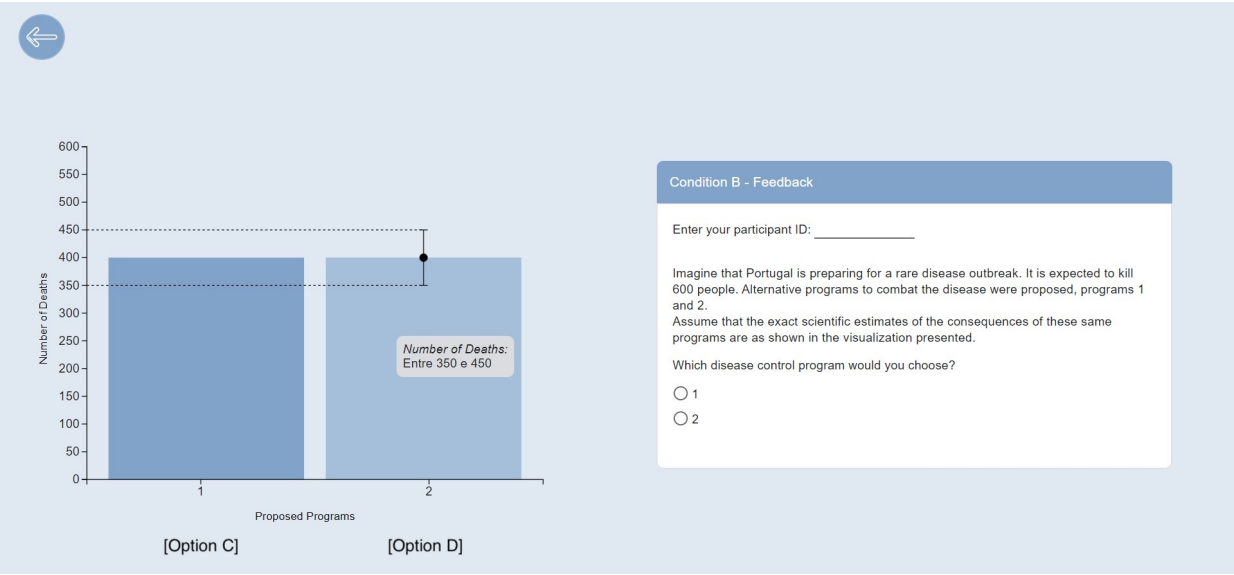


Fig. 2. The ***negative*** framing condition of the study, indicating the deaths for each option. In here, hovering a program and, therefore, showing the details about it. The specific options are annotated between square brackets on the image and were not shown to participants.

E. Procedure

We recruited 91 participants (51 females, 39 males, 1 other) aged 17 – 59 (M = 26.33, SD = 10.646). Due to constraints from COVID-19, we conducted each user test as a Zoom video meeting with one experimenter at a time. Each study session began with an introductory text including a description of what should be expected from the experiment and what would be asked of each participant. After consenting to the collection and further analysis of their data, participants answered the demographic questionnaire. Each individual was presented with a tutorial image of both idioms used, revealing how to interpret the data from each one. The explanatory images showed data unrelated to the problem of the study itself and that was, in addition, explicitly mentioned to the users to prevent potential biases. Once they finished the questionnaire and tutorials, the core phase of the experiment began. Each participant was randomly assigned to start with either the *positive* or *negative* framing condition and received the opposite one. We informed participants about the decision's context and available options for each framing condition. In particular, we prompted the individuals to pay attention to the expected values of both options. Once the session was over we would thank the participants for their time, explain the goal of the study – solely at the very end also to prevent bias – and store all the

information gathered in that session.

F. Data Analysis

Our experiment follows a within-subjects factorial design with two independent variables. The framing condition has two levels – *positive* or *negative*. Further, the risk factor also has two levels – *risky* or *not risky*. We used a two-way repeated measures ANOVA to determine if there are statistically significant main and interaction effects of the framing condition and the risk factor on the interaction volume. We also used one-way repeated measures ANOVAs to study the effects of the framing condition on the decision time and self-reported riskiness of the choice. Additionally, we used McNemar's test [39] with continuity correction [40] to determine if the framing strategies effectively primed individuals.

IV. Results

This section covers our study's results, tackling the framing context's effect on user interaction and decision-making. Figure 3 provides an overview of the descriptive statistics. As we mentioned, we randomized the order by which the participants were exposed to a frame. Our next step is understanding whether user interaction or decision-making allows us to check whether the individual was primed. Data are presented as mean $\pm$ standard error unless otherwise stated.

A. User Interaction

We analyze two user interaction metrics to understand whether the different frames affected how users interacted with the visualizations while deciding the program choices. First, we analyze the interaction volume, i.e., how many hover events participants triggered per program choice. We started by running a two-way within ANOVA to study the relationship between the frame and the risk factor of the option in the number of triggered hover events (Figure 4). We did not find an interacting effect between the framing condition and the risk factor of the program, $F(1, 90) = 0.266, p = .607$, partial $\eta^2 = .003$. However, we found a measurable main effect from the risk factor, $F(1, 90) = 10.637$, $p = .002$, partial $\eta^2 = .106$. In particular, participants triggered more hover events in the bar showcasing the risky option (3.214 ± 0.220) than in the bar showing the not risky option (2.835 ± 0.210) with a statistically significant increase of 0.379 (95% CI, 0.148 to 0.610) events, $p = .002$. Although the frame did not produce a statistically significant main effect, $F(1, 90) = 3.432, p = .067$, partial $\eta^2 = .037$, the p-value was close to the acceptance level. Participants triggered more hover events under the negative frame (3.247 ± 0.276) than under the positive frame (2.802 ± 0.197).

Second, we analyzed whether the framing affected the time users took to decide. We ran a one-way ANOVA with the frame as the independent variable. We found that the time users took to decide did not significantly vary between the frame conditions, $F(1, 90) = 2.351$, $p = .129$, partial $\eta^2 = .025$. However, results suggest that people were faster in the positive frame (45.035 ± 2.248 seconds) than in the negative frame (49.02 ± 2.874).

B. Riskiness of Choice

A one-way ANOVA showed a nonsignificant main effect of the frame on the self-reported choice riskiness, $F(1, 90) = 0.035$, $p = .853$, partial $\eta^2 < .001$. The results by frame suggest that people consider their choices in the positive frame as slightly less risky (3.99 ± 0.176) than those in the negative frame (4.02 ± 0.180).

C. Priming Effect

We started our analysis by looking at the choices in each framing condition (Table III). Data are mean $\pm$ standard deviation in this section. For the *positive* framing condition of the study, 58 participants (63.74%) chose the risky option (*B*), while 33 participants (36.26%) settled for the not risky one (*A*). We found a similar trend in the *negative* framing condition with 61 participants (67.03%) picking the risky program (*D*) and 30 participants (32.97%) opting not to take a risk in their choice (*C*). These changes were a consequence of 3.29% ($0.6703 - 0.6374 \times 100$) more participants choosing the risky option upon the *negative* framing condition of the study. However, we must examine the discordant pairs to study the framing effect. 19 participants went for the not risky option upon the *positive* framing condition, giving a different answer while in the *negative* one. Moreover, 16 participants chose the risky option during the *positive* framing condition of the study and opted for the not-risky one when in the *negative* framing condition.

We ran a McNemar's test [39] with continuity correction [40] to determine if there was a difference in the proportion of participants who took a risk in their choice between the *positive* and *negative* framing conditions. The proportion of participants who opted for the risky option increased from 63.74% in the *positive* framing condition to 67.03% in the *negative* one, a not statistically significant difference, $\chi^2(1) = 0.114, p = 0.735$. With this, we concluded that the proportion of participants who chose to risk did not (significantly) differ between framing conditions - *positive* and *negative*. Thus, we could not reject the null hypothesis as the test results indicated there is not sufficient evidence to say that the differences in the dichotomous dependent variable - *choice* - between two related groups - *positive* and *negative* conditions - were not equal. Moreover, a one-way within ANOVA shows that there is no statistically significant difference between the frame conditions regarding the self-assessed risk of the decision, $F(1, 90) = .035$, $p = .853$, partial $\eta^2 < .001$. In other words, we did not find significant evidence like Tversky and Kahneman [10]. Although results suggest that the framing strategies led participants to interact differently with the dashboard, minimizing the priming effect leads us to conclude that bar charts with error bars help mitigate the framing effect but not to a full extent.

V. Discussion

The gathered results prove that framing bias is worthy of further and deeper research within the InfoVis community.

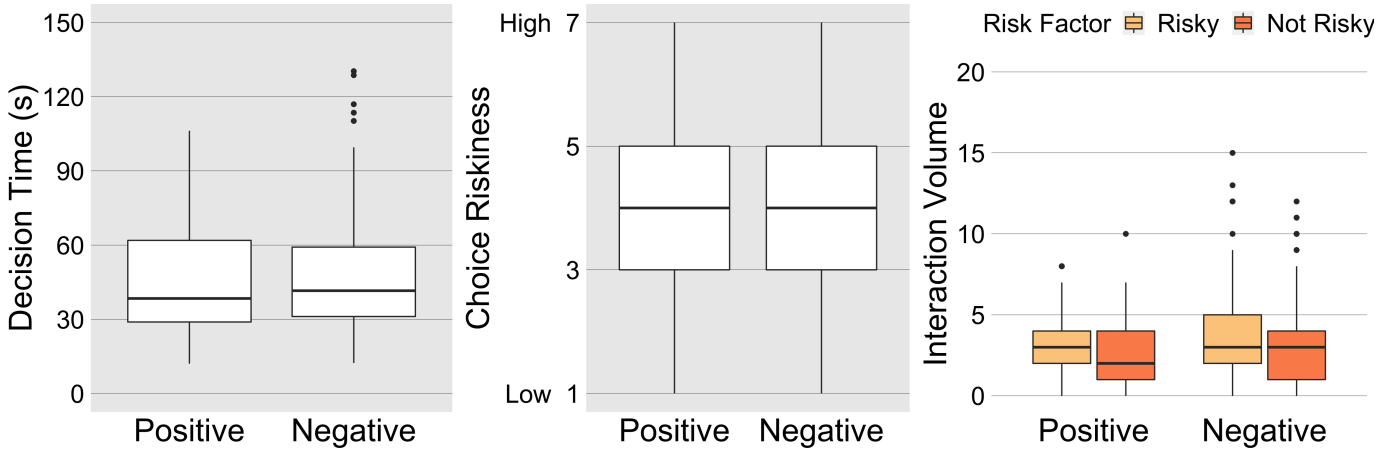


Fig. 3. Quantitative results of the experiment per framing condition and risk factor.

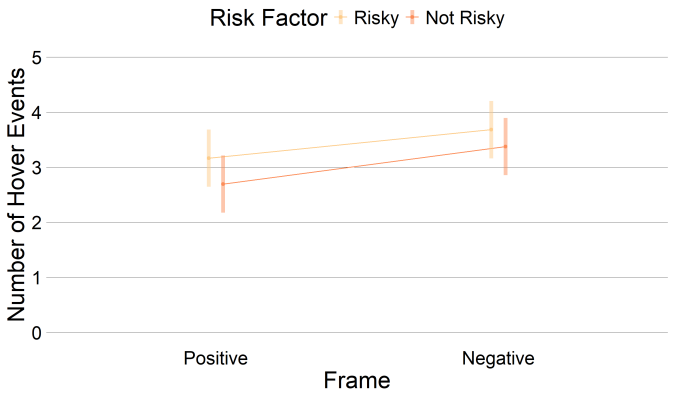


Fig. 4. Estimated marginal means of the number of hover events triggered in each option across framing conditions.

TABLE III
CROSSTABULATION OF THE DECISIONS BETWEEN THE FRAMING CONDITIONS. ADJUSTED RESIDUALS APPEAR IN PARENTHESES NEXT TO THE OBSERVED FREQUENCIES.

		Positive Framing		
		Risky	*Not Risky*	Total
Negative Framing	*Risky*	42 (1.4)	19 (−1.4)	61
	Not Risky	16 (−1.4)	14 (1.4)	30
	Total	58	33	91

In particular, when the core function of these systems is to support the human decision-making process.

A. Explanation of Findings

We decided to employ a simple dashboard containing a bar chart. For each framing context, we provided two possible hypotheses encoded as bars. Moreover, both hypotheses showed the same expected value. It means that the expected result will be the same independently of the participant's choice. In particular, one of the bars included the confidence interval lines to showcase that that hypothesis included some risk.

Looking at the participants' choices, we can observe that the *risky* option is taken 63.74% of the time in the positive frame and 67.03% in the negative frame. This result allows us to understand that **our sample user opts for a decision containing some risk**. However, the most exciting fact is related to the evident change between a *risky* and a *not risky* option based on the frame. Although the expected value is the same within each frame set, some people prefer to be risky in one frame and avoid risk in the other. Consequently, these **individuals were primed by the frame of the context**. Nevertheless, our results suggest that the framing techniques could only prime 38.5% of the individuals since 56 (61.5%) participants did not change their decision between frames.

The *negative* framing condition showed that most individuals opted to take a risk in their choice, having 61 out of the 91 subjects choosing option *D*. This result was in line with what was expected. However, the *positive* framing condition had the majority of participants also deciding on the risky option (*B*) - 58 out of the total of 91 participants in our study. Additionally - despite it not being a statistically significant find - the number of hovers was higher for the *negative* framing condition. As for the hovers between the *risky* and *not risky* options within each condition - *positive* and *negative* -, these were statistically significantly different. The *risky* options (*B* and *D*) withheld a higher number of hovers overall - possibly due to how it was the most chosen option in both framing conditions. This trend derives from the participants wanting to check the lower and upper bounds of the interval. Since the *not risky* bar encoded a fixed value, there was no need to check the absolute expected value frequently. However, our results also provide further insight by suggesting that **the negative frame led participants to trigger more hover events and spend more time deciding**. It hints that the testers weighted both options more when conferred with a negative frame. Moreover, the testers triggered more hover events in the bar, representing their choice in both frame settings. These exciting results may provide some *apriori* knowledge of how the decision will be made.

Regardless of it not being a statistically significant difference, the perceived risk of the choice taken in the *negative* framing condition was higher than the decision made in the *positive* one. Such occurrence aligns with the higher amount of time taken to choose in the *negative* study condition. Despite the difference between proportions not being significantly different, some participants appear to have been primed, reinforcing the possibility of framing bias within this context. All this evidences the importance of further exploring the framing bias within InfoVis systems to support the decision-making process better and avoid biased choices.

B. Experimental Implications

There is no consensus on what constitutes a good visualization to support decision-making, particularly when investigating the possible inherent framing bias present. We began our work with the initial problem that led to the discovery of this bias. Attempting to build on it and bring it into the InfoVis community, we plucked inspiration from the small body of research intersecting the decision-making process and visualization.

Studies that commonly focus on the effect of cognitive biases on decision-making present the decision problems through written or audio channels (e.g., [2], [10]). To the best of our knowledge, there is no measure to assess the framing bias of individuals. We considered the priming of individuals to be the changing of behavior. That is, the changing of opting for a *risk-taking* or *risk-averse* approach between the two main conditions of our work - *positive* and *negative* framings. With this framing strategy in mind, the obtained results suggest that **visualization may help individuals be less susceptible to the framing effect**. In particular, while Tversky and Kahneman [10] found that participants were significantly primed by the framing effect, depicting the possible choices through a bar chart alleviated the priming effect. Our study adds to other techniques used in the visualization research field to diminish the susceptibility to priming effects. For instance, Dimara et al. [20] countered the attraction effect by creating a feature to allow users to remove information from scatterplots that should not affect rational decision-making. As such, our work opens several opportunities to assess whether the countering effect of visualization transfers to other decision problems. Further, designers should include visualizations in decision-support systems to alleviate the framing effect.

C. Limitations and Future Work

The most significant limitation of our study stems from the lack of research concerning framing bias. In particular, there is no algorithmic measure to assess the framing effect and determine if individuals were affected by it and the quality of the decisions taken. Another limitation is that our results only apply to the specific context from which we derived the frames. Regarding user familiarity, most participants in our study were either familiar or very familiar with the bar chart visualization (M = 6.52, SD = 0.765). For the bar chart with the error bar, the self-reported familiarity levels were more scattered across the 7-point Likert scale used to assess it (M = 4.59, SD = 1.646). However, both familiarity levels are positive on the scale, and consequently, we can assume that individuals understood the visual encodings. Nonetheless, future work should account for the effect of visualization literacy in the framing bias. Another exciting measure to leverage is the self-reported overall risk attitude of the participants. Participants were more prone to follow risky strategies (M = 4.40, SD = 1.201). Future work should consider a more balanced sample.

Our research was merely able to encompass one chart type. It leaves room to explore further encodings - simple or complex - and other types of framing, problems, and distinct problem contexts. Regarding the experiment, using confidence intervals (CI) indicating two values rather than a fixed (not risky) one may have affected the number of hovers of each option. Thus, future work may also explore different ways to represent the uncertainty inherent to the different options presented to users [41], such as using probabilistic overlays like blurred regions or gradient shading, providing credibility bands, using glyph-based approaches like density plots, leveraging narrative techniques such as uncertainty annotations, or enabling interactivity to allow users to explore how uncertainty impacts their choices. Finally, complex thinking through visualization becomes more susceptible to individual characteristics [42]–[44]. It is possible to enrich the user profile of the decision-maker with dynamics from psychological constructs. In particular, InfoVis systems with access to personality data can detect if the decision-maker will be more susceptible to irrational decisions. In that case, the system can adapt its content or provide further assistance to counter the priming effect and, consequently, allow the user to make a (more) rational decision.

VI. Conclusions

While designing a visualization, one must consider three limitations: computers, displays, and humans. Not only is human vision limited, but human reasoning too. Hence, to begin to understand how visualizations can support humans, it is imperative to consider such pitfalls present within human judgment and decision-making and understand how these limitations might affect data visualization systems. Our exploratory study focused on this, with a particular aim to delve into the influence framing bias may have within the visualization community. Our results shed new light on understanding the framing bias within the InfoVis field, suggesting that leveraging bar charts with error bars helps mitigate the framing effect. We can use this knowledge to explore which visualization techniques prime individuals based on utility theory and devise a set of design guidelines to improve the design of visualization-based decision support systems.

Acknowledgments

This work was supported by national funds through Fundação para a Ciência e a Tecnologia (FCT),

grants SFRH/BD/144798/2019, UID/50021/2025, UID/PRR/50021/2025, and UID/315/2025.

REFERENCES

[1] H. A. Simon, *Models of man; social and rational.* Wiley, 1957.

[2] A. Tversky and D. Kahneman, "Judgment under uncertainty: Heuristics and biases," *science*, vol. 185, no. 4157, pp. 1124–1131, 1974.

[3] D. Kahneman, S. P. Slovic, P. Slovic, and A. Tversky, *Judgment under uncertainty: Heuristics and biases*. Cambridge university press, 1982.

[4] E. Dimara, S. Franconeri, C. Plaisant, A. Bezerianos, and P. Dragicevic, "A task-based taxonomy of cognitive biases for information visualization," *IEEE transactions on visualization and computer graphics*, 2018.

[5] E. Wall, L. M. Blaha, L. Franklin, and A. Endert, "Warning, bias may occur: A proposed approach to detecting cognitive bias in interactive visual analytics," in *2017 IEEE Conference on Visual Analytics Science and Technology (VAST)*. IEEE, 2017, pp. 104–115.

[6] E. Dimara, A. Bezerianos, and P. Dragicevic, "The attraction effect in information visualization," *IEEE transactions on visualization and computer graphics*, vol. 23, no. 1, pp. 471–480, 2016.

[7] ——, "Conceptual and methodological issues in evaluating multidimensional visualizations for decision support," *IEEE transactions on visualization and computer graphics*, vol. 24, no. 1, pp. 749–759, 2017.

[8] M. Bancilhon and A. Ottley, "Did you get the gist of it? understanding how visualization impacts decision-making," *arXiv preprint arXiv:2010.04096*, 2020.

[9] S. Plous, *The psychology of judgment and decision making.* Mcgraw-Hill Book Company, 1993.

[10] A. Tversky and D. Kahneman, "The framing of decisions and the psychology of choice," *science*, vol. 211, no. 4481, pp. 453–458, 1981.

[11] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," in *Handbook of the fundamentals of financial decision making: Part I*. World Scientific, 2013, pp. 99–127.

[12] H.-K. Kong, Z. Liu, and K. Karahalios, "Frames and slants in titles of visualizations on controversial topics," in *Proceedings of the 2018 CHI conference on human factors in computing systems*, 2018, pp. 1–12.

[13] R. H. Thaler, A. Tversky, D. Kahneman, and A. Schwartz, "The effect of myopia and loss aversion on risk taking: An experimental test," *The quarterly journal of economics*, vol. 112, no. 2, pp. 647–661, 1997.

[14] A. Dasgupta, J. Poco, Y. Wei, B. Cook, E. Bertini, and C. Silva, "Bridging theory with practice: An exploratory study of visualization use and design for climate model comparison," *IEEE Transactions on Visualization and Computer Graphics*, vol. 21, pp. 996–1014, 09 2015.

[15] Y. Zhang, R. K. Bellamy, and W. A. Kellogg, "Designing information for remediating cognitive biases in decision-making," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, ser. CHI '15. New York, NY, USA: Association for Computing Machinery, 2015, p. 2211–2220. [Online]. Available: https://doi.org/10.1145/2702123.2702239

[16] K. Eberhard, "The effects of visualization on judgment and decision-making: a systematic literature review," *Management Review Quarterly*, vol. 73, no. 1, pp. 167–214, 2023.

[17] T. Alves, R. Velhinho, J. Henriques-Calado, D. Gonçalves, and S. Gama, "Studying the resiliency of the anchoring bias to locus of control in visualization," *Information Visualization*, vol. 23, no. 1, pp. 67–83, 2024.

[18] C. Pereira, T. Alves, and S. Gama, "The phantom effect in information visualization," *Computers & Graphics*, vol. 125, p. 104109, 2024.

[19] J. Huber, J. Payne, and C. Puto, "Adding asymmetrically dominated alternatives: Viola-tions of regularity and the similarity hypothesi," *Journal of Consumer Research*, vol. 9, pp. 90–98, 02 1982.

[20] E. Dimara, G. Bailly, A. Bezerianos, and S. Franconeri, "Mitigating the attraction effect with visualizations," *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, pp. 850–860, 2019.

[21] A. K. Thomas and P. R. Millar, "Reducing the Framing Effect in Older and Younger Adults by Encouraging Analytic Processing," *The Journals of Gerontology: Series B*, vol. 67B, no. 2, pp. 139–149, 09 2011. [Online]. Available: https://doi.org/10.1093/geronb/gbr076

[22] M. A. Bedek, A. Nussbaumer, L. Huszar, and D. Albert, "Methods for discovering cognitive biases in a visual analytics environment," *Cognitive Biases in Visualizations*, pp. 61–73, 2018.

[23] T. Zuk and S. Carpendale, "Visualization of uncertainty and reasoning," in *International symposium on smart graphics*. Springer, 2007, pp. 164–177.

[24] G. Ellis and A. Dix, "Decision making under uncertainty in visualisation?" in *VDMU 2015: Workshop on Visualization for Decision Making under Uncertainty*, K. Potter and R. Westermann, Eds., 2015.

[25] C. Xiong, L. Van Weelden, and S. Franconeri, "The curse of knowledge in visual data communication," *IEEE transactions on visualization and computer graphics*, vol. 26, no. 10, pp. 3051–3062, 2019.

[26] J. Wood, D. Badawood, J. Dykes, and A. Slingsby, "Ballotmaps: Detecting name bias in alphabetically ordered ballot papers," *IEEE Transactions on Visualization and Computer Graphics*, vol. 17, no. 12, pp. 2384–2391, 2011.

[27] L. M. Padilla, S. H. Creem-Regehr, M. Hegarty, and J. K. Stefanucci, "Decision making with visualizations: a cognitive framework across disciplines," *Cognitive research: principles and implications*, vol. 3, no. 1, p. 29, 2018.

[28] K. C. Radley, E. H. Dart, and S. J. Wright, "The effect of data points per x-to y-axis ratio on visual analysts evaluation of single-case graphs." *School Psychology Quarterly*, vol. 33, no. 2, p. 314, 2018.

[29] K. E. Klockow-McClain, R. A. McPherson, and R. P. Thomas, "Cartographic design for improved decision making: Trade-offs in uncertainty visualization for tornado threats," *Annals of the American Association of Geographers*, vol. 110, no. 1, pp. 314–333, 2020.

[30] I. Alieva, "How american media framed 2016 presidential election using data visualization: The case study of the new york times and the washington post," *Journalism Practice*, vol. 17, no. 4, pp. 814–840, 2023.

[31] M. Friedman and L. J. Savage, "The utility analysis of choices involving risk," *Journal of political Economy*, vol. 56, no. 4, pp. 279–304, 1948.

[32] R. L. Keeney, H. Raiffa, and R. F. Meyer, *Decisions with multiple objectives: preferences and value trade-offs*. Cambridge university press, 1993.

[33] M. Bancilhon, Z. Liu, and A. Ottley, "Let's gamble: How a poor visualization can elicit risky behavior," *arXiv preprint arXiv:2010.14069*, 2020.

[34] G. Cumming, "The new statistics: Why and how," *Psychological science*, vol. 25, no. 1, pp. 7–29, 2014.

[35] C. F. Manski, "Communicating uncertainty in policy analysis," *Proceedings of the National Academy of Sciences*, vol. 116, no. 16, pp. 7634–7641, 2019.

[36] Y. Kwak and S. Huettel, "The order of information processing alters economic gain-loss framing effects," *Acta psychologica*, vol. 182, pp. 46–54, 2018.

[37] E. Gamliel, A. H. Zohar, and H. Kreiner, "Personality traits moderate attribute framing effects," *Social Psychological and Personality Science*, vol. 5, no. 5, pp. 584–592, 2014.

[38] A. Oehler and F. Wedlich, "The relationship of extraversion and neuroticism with risk attitude, risk perception, and return expectations." *Journal of Neuroscience, Psychology, and Economics*, vol. 11, no. 2, p. 63, 2018.

[39] Q. McNemar, "Note on the sampling error of the difference between correlated proportions or percentages," *Psychometrika*, vol. 12, no. 2, pp. 153–157, 1947.

[40] A. L. Edwards, "Note on the "correction for continuity" in testing the significance of the difference between correlated proportions," *Psychometrika*, vol. 13, no. 3, pp. 185–187, 1948.

[41] A. Kamal, P. Dhakal, A. Y. Javaid, V. K. Devabhaktuni, D. Kaur, J. Zaientz, and R. Marinier, "Recent advances and challenges in uncertainty visualization: a survey," *Journal of Visualization*, vol. 24, no. 5, pp. 861–890, 2021.

[42] C. Ziemkiewicz, A. Ottley, R. J. Crouser, A. R. Yauilla, S. L. Su, W. Ribarsky, and R. Chang, "How visualization layout relates to locus of control and other personality factors," *IEEE transactions on visualization and computer graphics*, vol. 19, no. 7, pp. 1109–1121, 2012.

[43] T. Delgado, T. Alves, and S. Gama, "How neuroticism and locus of control affect user performance in high-dimensional data visualization," *Computers & Graphics*, vol. 109, pp. 88–99, 2022.

[44] T. Alves, T. Delgado, J. Henriques-Calado, D. Gonçalves, and S. Gama, "Exploring the role of conscientiousness on visualization-supported decision-making," *Computers & Graphics*, vol. 111, pp. 47–62, 2023.