Visualizing Interaction Effects for Combinatorial Cost-Benefit Analysis

T. Bieg[1,3], I. Krottenberger[1], S. Knöttner[2], and M. Oppermann[1]

AIT Austrian Institute of Technology, Vienna, Austria. [1]Center for Technology Experience, [2]Center for Energy.
[3]WU Vienna University of Economics and Business, Vienna, Austria.

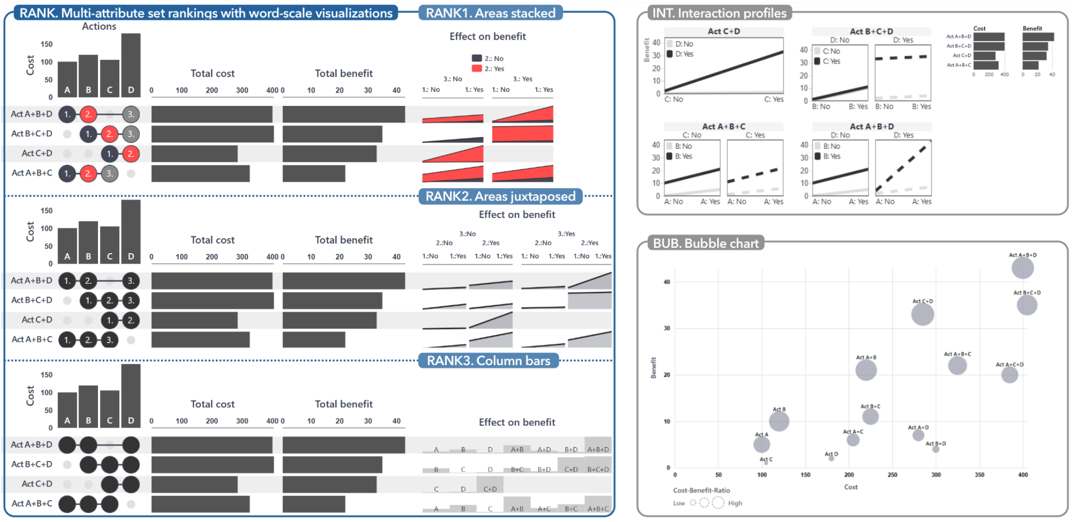

Figure 1: *Techniques for analyzing interaction effects in decision-making. RANK: Multi-attribute rankings with small-scale visualizations, with three variants: RANK1: Stacked areas, RANK2: Juxtaposed areas, RANK3: Column bars. INT: Interaction plots. BUB: Bubble chart.*

Abstract

Interaction effects occur when the combined impact of multiple actions differs from the sum of their individual effects. This creates challenges for scenarios that require analyzing how different combinations of actions affect an outcome of interest (i.e., combinatorial cost-benefit analysis). Visualization techniques support interpretation, but most existing approaches rely on multi-series line charts (interaction plots), which are widely used but do not explicitly support comparing interaction effects across alternative action sets. Accordingly, we investigate visualization approaches for analyzing interaction effects in combinatorial cost-benefit analysis. We propose a method integrating multi-attribute set rankings with small-scale visualizations to facilitate comparative analysis. Through a user study, we evaluate the effectiveness of three techniques for representing two- and three-way interactions. We present preliminary findings and discuss design implications to inform future visualization research.

CCS Concepts

• ***Human-centered computing** → **Visualization techniques; Visualization design and evaluation methods;***

1. Introduction

Decision-making often involves selecting among multiple potential actions, each associated with distinct costs and benefits. These scenarios require analyzing how different combinations of possible actions may affect the outcome of interest, which we refer to as combinatorial cost-benefit analysis (CCBA) [Cam86]. CCBA is common to many practical settings that involve substantial investments or risks—such as policy-making, financial portfolio management, industrial transformation, or health care. A central challenge of CCBA is rooted in interaction effects [RR89] which arise when the combined effect of two or more actions differs from the sum of their individual effects, leading to non-trivial outcomes [Has09]. In the presence of interaction effects, the analysis extends beyond evaluating individual actions in isolation as actions may influence one another in unexpected ways. Thus, interpreting interaction effects can be challenging, particularly for people who may have limited experience with statistical methods [MKK18].

Given the practical relevance and challenging nature of such scenarios, there is a need for finding ways to support a better understanding of interactions effects in CCBA settings and guide informed decision-making. Visualization techniques provide a means to explore large decision spaces [SHB*14], compare multi-attribute actions [GLG*13], and facilitate the interpretation of complex relationships. However, the visual analysis of interaction effects in the context of CCBA remains a largely unexplored topic. Addressing this need, we investigate visualization techniques for analyzing interaction effects in CCBA contexts through a domain-agnostic approach. Specifically, we address the following research questions:

- **RQ1:** Which visualization techniques are suitable for the analysis of interaction effects in the context of CCBA?
- **RQ2:** What challenges and design implications arise when visualizing interaction effects in combinatorial decision-making?

Our contributions include (1) a visualization approach for analyzing interaction effects within ranked combinations of actions, (2) findings from a preliminary comparative study evaluating the effectiveness of three visualization techniques in representing two- and three-way interaction effects, and (3) design considerations for visualizing interaction effects to inform future visualization research and offer practical guidance. We provide additional details on the review of techniques, source code, and enlarged figures as supplemental materials at osf.io/zkthj/.

2. Related Work

Accounting for interaction effects is essential in combinatorial decision-making across various domains, including portfolio analysis [MLK*24], public health [PG24, Gre09, GGO*22], and machine learning [IPH22]. However, analyzing these effects remains challenging due to statistical complexity and interpretability issues. Statistical methods, such as slope difference tests [DR06, JWT90], help to detect effects quantitatively, but their results can be difficult to interpret and communicate effectively.

The interaction plot (factorial plot, main effects plot) [MKK18, BB99] is most commonly used to show two-way interactions, typically by displaying outcome curves for different conditions on the same axes. It can be extended to three-way interactions by using side-by-side charts. Murphy et al. [MA22] highlighted challenges regarding the interpretability of these plots. McCabe et al. [MKK18] provided tools and guidelines for interaction plots, and others suggested interactive interaction plots [SEG*15] embedded in a coordinated multiple views system [Rob07]. The compass plot [BSR00] visualizes combinatorial effects in evolutionary algorithms, but can be applied to other domains. Additionally, Bjorheim et al. [BTW09] discuss a visual method for cost-effectiveness comparisons but do not show interaction effects explicitly.

In a broader context, numerous visualization systems have been developed to support decision-making [PCRHS18] and the analysis of multidimensional parameter spaces [SHB*14]. VISPUR [TAL23] aids in interpreting associations and identifying spurious paradoxes, while INTERACT [CMPG24] is a visual what-if analysis tool for regression models, including statistical interactions between features. In machine learning, techniques such as partial dependence plots [Fri01], Shapley Additive Explanations (SHAP) [LEL18], and Individual Conditional Expectation (ICE) plots [GKBP15] are commonly used to examine interaction effects within complex models. VINE [Bri19] enhances these methods by incorporating clustering and ICE/PDF plots to provide regional explanations of models. However, these methods are designed for feature interactions in predictive modeling, where attributes are mostly continuous, and differ from the problem setting and data characteristics addressed in this work.

Other approaches are interaction surface plots [LSKK12], contour plots [Miz19], cube plots [Mon17], and heatmaps [HRVdLN*15]. While these visualizations effectively illustrate pairwise interactions, they are often limited when it comes to comparing interaction effects between alternative sets of actions—a key requirement in many decision-making scenarios. We discuss these competing visual encodings in Sec. 4.1 and take a step toward addressing this gap by introducing a technique tailored to such comparisons.

Our work is also related to set-based visualization techniques, including mosaic plots [Fri99], PowerSet [AR16], AggreSet [YEB15], and Radial Sets [AAMH13]. While these methods effectively depict set relationships and intersections, they do not explicitly support the analysis of interaction effects. Our approach builds upon UpSet [LGS*14] by integrating small-scale visualizations [HBKE22], similar to word-scale visualizations [GWFI14], to enable direct comparison of interaction effects between more than two alternative sets of measures.

3. Task and Data Characterization

Questions related to selecting the most effective decarbonization measures in the brick and ceramic industry initially motivated and guided our investigation. We abstracted domain-specific challenges into a more general analytical scenario (see Fig. 2), where decision-makers must identify the optimal cost-benefit trade-off under given constraints while gaining insight into underlying interaction effects. To support this analysis, we identified four key tasks:

T1: **Detect** interaction effect
T2: **Characterize** interaction type
T3: **Estimate** interaction strength
T4: **Compare** sets that may inhibt interaction effects

Rather than focusing solely on selecting the *best* set, which a simple ranking could achieve, these tasks emphasize understanding interaction effects to support a more informed decision-making. These abstract tasks guided our design process and evaluation.

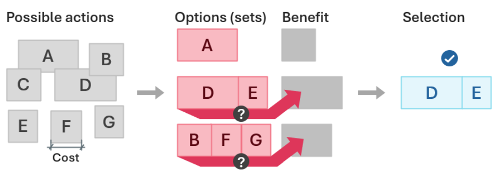

Figure 2: *Example analysis (e.g., reduce CO_2 emissions): rank action sets, analyze interactions, and select optimal option.*

In terms of data abstraction, we frame the problem with the following assumptions: Each action is represented as a binary variable, and each set contains a maximum of three actions. When all actions are inactive (zero), the interaction effect and baseline level are zero. Costs are independent, meaning each action has an associated cost that does not change when combined with other actions. Additionally, there is no time-dependent or sequential influence. The outcome, or interaction effect, is measured on a consistent scale across all sets. This framing balances a realistic analysis scenario with a manageable number of combinations and interaction complexity. We discuss the limitations in Sec. 6.

4. Visualization Techniques

We review existing techniques to identify potential limitations in CCBA contexts and, on this basis, introduce a new method.

4.1. Review of Visualization Techniques

In the context of our data and task abstractions, we assessed competing visual encodings. Our review first focuses on techniques for representing individual two- and three-way interactions and then examines options for comparing interaction effects across different action sets. Our selection is not exhaustive but represents a sample of visualization techniques derived from related work across various domains, that covers diverse visual encodings (see SUP-1).

For three-way interaction effects, we reviewed interaction plots, bubble charts, cube plots, and concentric circles. For two-way interactions, 3D surface plots, heatmaps, and node-link diagrams. Besides interaction plots, most techniques offer limited support for estimating the magnitude of interaction effects (Task T3). Similarly, comparisons of effects across alternative action sets remain largely unsupported, except through small multiples (T4). These limitations motivated the development of an alternative approach, as outlined in the following section.

4.2. Multi-Attribute Set Rankings with Small-Scale Visualizations

We propose an adaptation of UpSet [LGS*14] to better facilitate comparisons of interaction effects across alternative sets. UpSet is widely used to analyze relationships between sets which makes it well-suited for our scenario. It uses a matrix layout where each row corresponds to a unique intersection of set elements. We retain UpSet's original combination matrix on the left side, which encodes set memberships. The layout allows to display additional columns with properties of set intersections. We build upon this flexibility to construct a multi-attribute ranking and display the *total cost* and *total benefit* for each row (i.e., combination of actions). Additionally, we embed small-scale visualizations to represent interaction effects within the ranking. We explore three variants:

- **Areas (stacked):** Miniature representations of interaction profiles. The first variable is encoded on the x-axis, the second is represented by color, and for three-way interactions, the third is shown as a separate column (see Fig. 1-RANK1).
- **Areas (juxtaposed):** A modification of the stacked variant, where the second variable is also shown as a separate column instead of being encoded by color (see Fig. 1-RANK2).
- **Column chart:** Outcomes are shown as column heights and allows users to compare individual and combined effects (e.g., Set C+D in Fig. 1-RANK3).

5. Preliminary Comparative Evaluation

5.1. Methodology

While different techniques to visualize interactions have been proposed in the literature, evaluations focusing on their practical utility from a user perspective are rare. To address this, we conducted an online survey employing a quantitative between-subjects design with four experimental conditions. Based on the key tasks outlined in Sec. 3, we developed a CCBA scenario in which participants were provided with varying visual encodings (one technique per condition) of the same data. Through random allocation of participants to the experimental conditions, this design allows for a user-centred comparison of different visualization techniques in terms of performance-oriented and subjective metrics.

Based on our literature review, we selected two established techniques for visualizing interaction effects: bubble charts (BUB) and interaction profiles (INT). Additionally, we included a novel technique based on multi-attribute set rankings with small-scale visualizations in two variants: areas juxtaposed (RANK2) and column bars (RANK3). A pilot study indicated that these two variants may be more understandable than stacked areas. Fig. 1 provides an overview of the different visualization techniques.

5.1.1. Measures

To characterize the participants, we included questions on basic demographic attributes (age, gender) and prior experience with data visualizations (measured on a five-point scale with one item per plot type: line chart, box plot, tree map, bubble chart, bar chart), inspired by the Mini-VLAT [PO23] visualization literacy test.

To provide insight into the practical utility of the different visualization techniques, we chose a mix of performance-oriented and subjective task metrics. We included seven statements (either correct or incorrect) about interaction effects visualized in the plot (e.g., *"The total benefit of the combination of A1 and A2 is greater than the sum of the total benefit of A1 and A2 when applied individually."*). Participants were instructed to select correct statements as swiftly and accurately as possible (based on the visualization). We measured the time participants needed to complete the task and collected data on subjective task load (using the NASA task load index [Har06]). Moreover, we included items to assess subjective usefulness (*"The visualizations were useful."*) and comprehensibility (*"The visualizations were easy to understand."*) [HJCM20].

5.1.2. Participants

A total of 296 participants from the US (recruited via Prolific) completed the study and passed the attention check at the beginning of the survey. They received monetary compensation for their participation. To avoid harmful influences of outliers, we excluded participants whose completion time was 1.5 inter-quartile ranges below the first quartile or above the third quartile (n = 25). Thus, the final sample consists of 271 participants (mean age = 36.34 years; 49.4% female, 49.1% male, 1.5% diverse). The sample reported moderate familiarity with data visualizations (M = 3.09, SD = 0.80), which did not significantly differ between experimental groups.

5.1.3. Procedure and Data Analysis

After providing their informed consent, participants were randomly allocated to one of four experimental conditions (one per visualization technique). Next, they read a scenario in which they had to decide on a set of four actions to reduce greenhouse gas emissions. They were told that it is possible to implement a combination of one to three actions (not all four actions). In the following, they had time to inspect the plot visualizing the effects of different actions (including interaction effects). Participants were informed that on the next page, they will have to review a set of statements and give their best effort to decide which of them are correct (based on the plot shown). When continuing, the respective plot was displayed again alongside the different statements. After reviewing the statements, subjects answered additional questions on task load, usefulness, and comprehensibility. Materials and instructions used in our study are provided in the supplemental materials (SUP-2).

Survey data was processed and analyzed using R 4.1.2 [R C23]. For group comparisons, we computed the sum of correctly identified statements (range from 1 to 7) and the ratio between the number of correctly identified statements and task time. Moreover, a mean score for task load was calculated (range 1 to 100).

5.2. Results

	RANK2	RANK3	INT	BUB
Performance	5.04	4.62	4.54	**5.09**
Performance by task time	14.22	13.91	10.56	**14.75**
Task load	**66.73**	69.80	71.75	67.26
Comprehensibility	**5.06**	4.74	4.21	4.90
Usefulness	**5.86**	5.54	5.39	5.54

Table 1: *Mean values of performance-oriented and subjective task metrics by experimental conditions. For each metric, the "best-performing" condition is highlighted in* ***bold****. Performance describes the average number of correctly identified statements.*

Table 1 shows mean values of task metrics by experimental conditions (see Sec. 5.1 for detailed descriptions of conditions). Based on descriptive comparisons, BUB performs best in terms of performance-oriented metrics (highest average number of correctly identified statements, highest average number of correctly identified statements by task time). In terms of subjective metrics (task load, usefulness, comprehensibility), RANK2 (rankings with juxtaposed areas) consistently performs best. RANK2 also performs second best in terms of performance-oriented metrics. Moreover, INT performs the worst across all task metrics. While these patterns are highly consistent across conditions, it is important to highlight that they only represent descriptive trends as differences between conditions did not reach statistical significance.

6. Discussion

Driven by the need to support decision-making in CCBA scenarios, we investigated techniques for visualizing interactions through a domain-agnostic approach. We reviewed visual encodings for representing interaction effects, and proposed a novel method that integrates multi-attribute set rankings with small-scale visualizations. Further, we conducted a user study that offers preliminary findings on the effectiveness of different visualization approaches.

While our paper takes a first step towards improved visualizations for complex decision-making scenarios involving interaction effects, several limitations need to be considered. First, the present paper employed simplified data and task characteristics. Specifically, we only considered binary actions and did not include interaction effects on costs (only on benefits). While these simplifications are useful for comparing different visualization techniques in a standardized way, CCBA scenarios in practice can be even more complex [Gre09]. Second, some of the encodings used are not scalable beyond three-way interactions. Third, while the comparative evaluation can serve as a basis for further research, it only provides preliminary findings. In particular, it only focused on a specific task, did not involve qualitative feedback, and limited statistical power may have prevented detecting significant differences between groups.

Acknowledging these constraints, our paper offers useful guidance for visualization design. Specifically, beyond introducing a novel technique based on multi-attribute set rankings, our review of different techniques provides a comprehensive overview of methods suitable for visualizing interactions (see Fig. 1 in SUP-1). Researchers and practitioners can use this overview as a basis to create interaction visualizations tailored to specific use cases.

The present study also offers directions for further research on visualizing interaction effects to support decision-making. Traditional interaction profiles are commonly used in scientific literature [MKK18]. However, the question regarding their usefulness in practical decision-making scenarios (including CCBA contexts) remains open. Our preliminary comparative evaluation indicates that, in fact, interaction profiles may not be superior to alternative visual encodings. Other methods could be more useful for practical purposes—a hypothesis to be validated by further research.

Furthermore, given that CCBA in practical decision-making scenarios still remains complex, there is room for research to explore approaches beyond static visualizations to guide informed decision-making. Building upon techniques proposed in this paper and combining them with interactive visualization approaches may present a promising research direction with substantial practical impact. Such approaches could also provide solutions for scaling visualizations in terms of the number of measures, decision sets, and variable types (e.g., categorical versus continuous actions).

7. Conclusions

In conclusion, this paper takes steps towards a better understanding of visualizations for decision-making scenarios involving interaction effects. We compare alternative approaches and offer directions for future research. In doing so, we hope to inspire further research that can build on our study to provide improved visualizations for complex decision-making in practice.

8. Acknowledgements

This publication has been conducted within the project *Green-Bricks* (FFG no. 999894581). The project is supported with funds from the Austrian Climate and Energy Fund and implemented in the framework of the RTI-initiative *Flagship Region Energy*.

References

[AAMH13] ALSALLAKH B., AIGNER W., MIKSCH S., HAUSER H.: Radial sets: Interactive visual analysis of large overlapping sets. *IEEE Trans. Visualization a. Computer Graphics 19*, 12 (2013), 2496–2505. 2

[AR16] ALSALLAKH B., REN L.: Powerset: A comprehensive visualization of set intersections. *IEEE Trans. Visualization a. Computer Graphics 23*, 1 (2016), 361–370. 2

[BB99] BARTON R. R., BARTON R. R.: Design-plots for factorial and fractional-factorial designs. *Graphical Methods for the Design of Experiments* (1999), 55–92. 2

[Bri19] BRITTON M.: VINE: Visualizing statistical interactions in black box models. *arXiv preprint 1904.00561* (2019). 2

[BSR00] BUDSABA K., SMITH C. E., RIVIERE J. E.: Compass plots: a combination of star plot and analysis of means to visualize significant interactions in complex toxicology studies. *Toxicology Methods 10*, 4 (2000), 313–332. 2

[BTW09] BJORHEIM A., TERJE A., WILLY R.: A new visualizing tool for communicating cost-effectiveness of safety measures. *Journal of Polish Safety and Reliability Association 1* (2009). 2

[Cam86] CAMPEN J. T.: *Benefit, Cost, and Beyond: The Political Economy of Benefit-Cost Analysis*. Ballinger Publishing Company, 1986. 1

[CMPG24] CIORNA V., MELANÇON G., PETRY F., GHONIEM M.: Interact: A visual what-if analysis tool for virtual product design. *Information Visualization 23*, 2 (2024), 123–141. 2

[DR06] DAWSON J. F., RICHTER A. W.: Probing three-way interactions in moderated multiple regression: development and application of a slope difference test. *Journal of Applied Psychology 91*, 4 (2006), 917. 2

[Fri99] FRIENDLY M.: Extending mosaic displays: Marginal, conditional, and partial views of categorical data. *Computational and Graphical Statistics 8*, 3 (1999), 373–395. 2

[Fri01] FRIEDMAN J. H.: Greedy function approximation: a gradient boosting machine. *Annals of Statistics* (2001), 1189–1232. 2

[GGO*22] GAROFALO S., GIOVAGNOLI S., ORSONI M., STARITA F., BENASSI M.: Interaction effect: Are you doing the right thing? *PLoS One 17*, 7 (2022). 2

[GKBP15] GOLDSTEIN A., KAPELNER A., BLEICH J., PITKIN E.: Peeking inside the black box: Visualizing statistical learning with plots of individual conditional expectation. *Computational and Graphical Statistics 24*, 1 (2015), 44–65. 2

[GLG*13] GRATZL S., LEX A., GEHLENBORG N., PFISTER H., STREIT M.: LineUp: Visual analysis of multi-attribute rankings. *IEEE Trans. Visualization a. Computer Graphics 19*, 12 (2013), 2277–2286. 2

[Gre09] GREENLAND S.: Interactions in epidemiology: relevance, identification, and estimation. *Epidemiology 20*, 1 (2009), 14–17. 2, 4

[GWFI14] GOFFIN P., WILLETT W., FEKETE J.-D., ISENBERG P.: Exploring the placement and design of word-scale visualizations. *IEEE Trans. Visualization a. Computer Graphics 20*, 12 (2014), 2291–2300. 2

[Har06] HART S. G.: Nasa-task load index (nasa-tlx); 20 years later. In *Proc. Human factors and ergonomics society* (2006), vol. 50, Sage publications Sage CA: Los Angeles, CA, pp. 904–908. 3

[Has09] HASTIE T.: The elements of statistical learning: data mining, inference, and prediction, 2009. 1

[HBKE22] HUTH F., BLASCHECK T., KOCH S., ERTL T.: Animated transitions for small-scale visualizations. In *Proc. Int. Symp. Visual Information Communication and Interaction* (2022), pp. 1–8. 2

[HJCM20] HINDALONG E., JOHNSON J., CARENINI G., MUNZNER T.: Towards rigorously designed preference visualizations for group decision making. In *IEEE PacificVis* (2020), IEEE, pp. 181–190. 3

[HRVdLN*15] HAARMAN B. C. B., RIEMERSMA-VAN DER LEK R. F., NOLEN W. A., MENDES R., DREXHAGE H. A., BURGER H.: Feature-expression heat maps. *Journal of Biomedical Informatics 53* (2015), 156–161. 2

[IPH22] INGLIS A., PARNELL A., HURLEY C. B.: Visualizing variable importance and variable interaction effects in machine learning models. *Computational and Graphical Statistics 31*, 3 (2022), 766–778. 2

[JWT90] JACCARD J., WAN C. K., TURRISI R.: The detection and interpretation of interaction effects between continuous variables in multiple regression. *Multivariate Behavioral Research 25*, 4 (1990), 467–478. 2

[LEL18] LUNDBERG S. M., ERION G. G., LEE S.-I.: Consistent individualized feature attribution for tree ensembles. *arXiv preprint 1802.03888* (2018). 2

[LGS*14] LEX A., GEHLENBORG N., STROBELT H., VUILLEMOT R., PFISTER H.: UpSet: visualization of intersecting sets. *IEEE Trans. Visualization a. Computer Graphics 20*, 12 (2014), 1983–1992. 2, 3

[LSKK12] LAMINA C., STURM G., KOLLERITS B., KRONENBERG F.: Visualizing interaction effects: a proposal for presentation and interpretation. *Journal of Clinical Epidemiology 65*, 8 (2012), 855–862. 2

[MA22] MURPHY K. R., AGUINIS H.: Reporting interaction effects: Visualization, effect size, and interpretation. *Journal of Management 48*, 8 (2022), 2159–2166. 2

[Miz19] MIZE T. D.: Best practices for estimating, interpreting, and presenting nonlinear interaction effects. *Sociological Science 6* (2019), 81–117. 2

[MKK18] MCCABE C. J., KIM D. S., KING K. M.: Improving present practices in the visual display of interactions. *Advances in Methods and Practices in Psychological Science 1*, 2 (2018), 147–165. 2, 4

[MLK*24] MUSTAJOKI J., LIESIÖ J., KAJANUS M., ESKELINEN T., KARKULAHTI S.: A portfolio decision analysis approach for selecting a subset of interdependent actions. *Science of the Total Environment 912* (2024), 169548. 2

[Mon17] MONTGOMERY D. C.: *Design and analysis of experiments*. John Wiley & Sons, 2017. 2

[PCRHS18] PADILLA L. M., CREEM-REGEHR S. H., HEGARTY M., STEFANUCCI J. K.: Decision making with visualizations: a cognitive framework across disciplines. *Cognitive research: principles and implications 3* (2018), 1–25. 2

[PG24] PEARCE N., GREENLAND S.: Confounding and interaction. In *Handbook of Epidemiology*. Springer, 2024, pp. 1–31. 2

[PO23] PANDEY S., OTTLEY A.: Mini-VLAT: A short and effective measure of visualization literacy. *Computer Graphics Forum 42*, 3 (2023), 1–11. 3

[R C23] R CORE TEAM: *R: A Language and Environment for Statistical Computing. Version 4.2.1*. R Foundation Statistical Computing, 2023. 4

[Rob07] ROBERTS J. C.: State of the art: Coordinated & multiple views in exploratory visualization. In *Int. Conf. on Coordinated and Multiple Views in Exploratory Visualization* (2007), IEEE, pp. 61–71. 2

[RR89] ROSNOW R. L., ROSENTHAL R.: Definition and interpretation of interaction effects. *Psychological Bulletin 105*, 1 (1989), 143. 1

[SEG*15] SPLECHTNA R., ELSHEHALY M., GRAČANIN D., URAS M., BÜHLER K., MATKOVIĆ K.: Interactive interaction plot: Supporting parameter space exploration in a design phase. *The Visual Computer 31* (2015), 1055–1065. 2

[SHB*14] SEDLMAIR M., HEINZL C., BRUCKNER S., PIRINGER H., MÖLLER T.: Visual parameter space analysis: A conceptual framework. *IEEE Trans. Visualization a. Computer Graphics 20*, 12 (2014), 2161–2170. 2

[TAL23] TENG X., AHN Y., LIN Y.-R.: VISPUR: Visual aids for identifying and interpreting spurious associations in data-driven decisions. *IEEE Trans. Visualization a. Computer Graphics* (2023). 2

[YEB15] YALCIN M. A., ELMQVIST N., BEDERSON B. B.: AggreSet: Rich and scalable set exploration using visualizations of element aggregations. *IEEE Trans. Visualization a. Computer Graphics 22*, 1 (2015), 688–697. 2