Visualizing Opinion Space in Voting Advice Applications: A User Study

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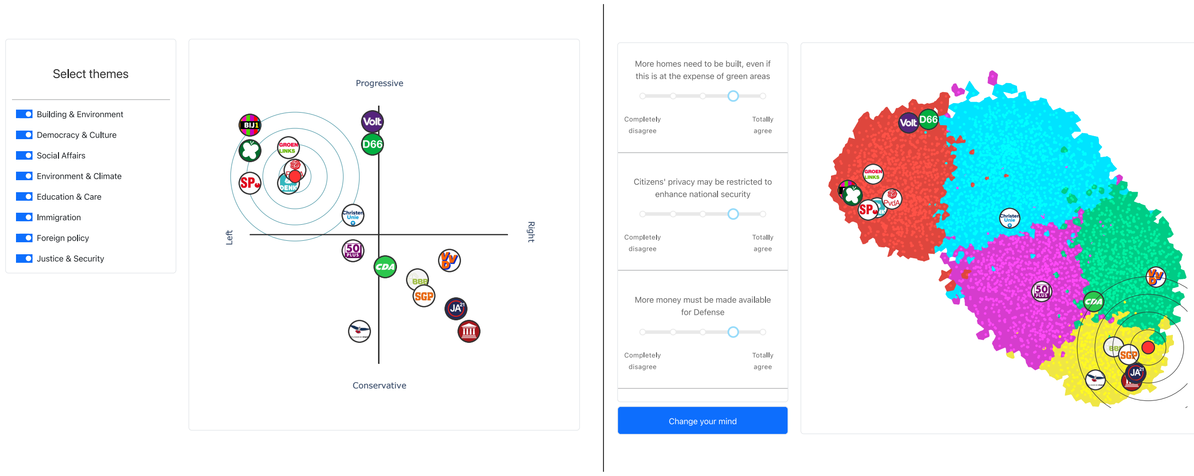

Figure 1: Two out of the three experimental conditions. On the left: the *control condition* – copy of the design used by Kieskompas, composed by the visualization referred to as *political compass* and *toggle buttons*. The parties and the user (red dot) are positioned with respect to two axes: left-right, progressive-conservative. The questions are grouped into thematic topics and the topics can be switched on and off using toggle buttons. On the right: the *experimental condition* – composed of the visualization referred to as *metaphoric map* and the *interactive sliders*. The metaphoric map shows positions of other voters participating in the elections (light dots), positions of the parties and the user (red dot). The colored clusters group voters with similar positions. The sliders allow to change the answers on the questions and see how the position of the user is adapted. (Original text on the interface were in Dutch.)

Abstract

We investigate the impact of visualization methods and interaction mechanisms in Voting Advice Applications (VAAs) by comparing two designs: the traditional design in Kieskompas [1] and an alternative design composed by a visualization – metaphoric map – based on dimensionality reduction of opinion data and an interaction mechanism allowing to adjust answers on the questions. In a user study with 382 participants from the Netherlands, we assessed their effects on vote choice, political knowledge, ease of use, and interpretation of opinion space. The results show no evidence that visualization and interaction mechanisms influence vote choice. The metaphoric map led to lower perceived and factual political knowledge and was harder to interpret, likely due to its higher visualization literacy demands. Notably, participants using metaphoric map offered more objective, non-ideological interpretations of their political position, suggesting potential to foster unbiased political comprehension. Supplementary materials are available at: https://osf.io/zvhsg/?view_only=ee2d7d315c254b358b9be077214cc18e.

Index Terms: VAAs, visualization, interaction, dimensionality reduction, social information, voting.

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1 Introduction & Related Work

Voting Advice Applications (VAAs) designed to support electorates ahead of elections, originated in the Netherlands in 1989 [12] and have since spread globally. In a VAA, users express their opinions on a set of political questions; the tool then matches them with political parties based on response similarity. Results are typically shown as ranked lists or visual summaries, helping users identify which party aligns most closely with their views. The main goal of VAAs is to support democratic participation by increasing voter turnout, political knowledge, and informed vote choice [12].

Although VAAs are used by millions, their impact remains limited [12, 23]. Some studies estimate VAAs influence 2–12% of voter turnout [9], while others view this as an overestimate [23]. More consistently, VAAs appear to enhance users' political (issue) knowledge [22].

Research on how VAAs visualize results remains relatively scarce [7, 13]. In an unpublished comparative study [13], Harks found that among common visual formats – *bar charts*, *spider graphs*, and *political compasses* – the political compass had the strongest influence on vote intention. Compass visualizations (see Fig. 1), as used in Kieskompas [2], iVoter [21], Vaalikone [4], Parteienavi [3], Vote Compass [5], and euandi [1], typically plot parties along two axes: economic (left–right) and cultural (conservative–progressive). However, this two-dimensional model has been criticized as reductive [26], omitting dimensions such as attitudes toward the EU, globalization, or national identity [6, 20, 34].

In response, newer VAAs incorporate alternative or multidimensional models, derived theoretically or empirically, though both approaches face critiques [6, 34].

VAAs typically rely on 30–36 policy statements [15, 27, 31, 32, 33], resulting in high-dimensional data that is difficult to present accessibly [7]. While ranked lists and 2D maps remain common, data visualization techniques such as dimensionality reduction scatterplots are increasingly used for their ability to preserve structure while remaining interpretable [7, 26].

Dimensionality reduction scatterplots enhanced with clustering and grouped regions are often referred to as *metaphoric maps* (see Fig. 1) or *map-like visualizations* [14]. These visualizations leverage the familiar geographic map metaphor and users' intuitive spatial reasoning. Metaphoric maps have demonstrated advantages over plain scatterplots in terms of user engagement [28] and task performance [29].

Beyond VAAs, recent visualization research has explored the impact of design in other civic contexts, such as election forecasting under uncertainty [35, 36] and participatory budgeting processes [16]. These studies also underscore how visual design influences interpretation, trust, and participatory behavior, reinforcing the broader civic relevance of visualization design choices.

In this paper, we examine how a metaphoric map-based VAA compares to the traditional political compass approach used in Kieskompas. We focus on users' vote choice, political knowledge, ease of use, and interpretation of their position in the opinion space.

2 USER STUDY

This section details the user study in which we investigated how different visualization and interaction designs in VAAs influence vote choice and political knowledge. We first describe the experimental conditions, followed by the participants, measurements, and procedure.

2.1 Experimental conditions

There were three conditions (see the video in the Supplementary Materials on OSF): *control* (political compass + toggles), *experimental* (metaphoric map + sliders), see Fig. 1 and *intermediate* (compass + sliders), see Fig.1 in the supplementary material.

Visualization Design. The political compass (PC) uses two predefined ideological axes – economic (left-right) and cultural (conservative-progressive) – to position users and parties. In contrast, the metaphoric map (MM) applies t-SNE to embed user responses based on similarity across all 30 political statements, producing a 2D layout that preserves local structure. This data-driven projection reveals clusters of users with similar opinions and allows for more nuanced spatial relationships beyond fixed axes. As a consequence of the embedding process, prior VAA user responses (n = 37,083) are also visualized as background dots, offering implicit social context that can counter cognitive biases [18, 19]. These crowd data points were not explicitly manipulated but are an inherent feature of the metaphoric map representation. Cluster regions were computed using K-means and displayed using Voronoi diagram. To reduce interpretive bias, we assigned cluster colors from a categorical palette selected for perceptual distinctness, explicitly avoiding political charged hues.

Interaction mechanisms. In Kieskompas' original design [2], 30 questions are grouped into themes. Users can toggle each group's influence, which triggers recalculation of party and user positions.

Based on discussions with Kieskompas designers, we know VAA users often revisit questions to test if small changes affect their position on the compass. This brings us an alternative design for the interaction mechanism – *interactive sliders* – that allow the user quickly adjust their answer on one of the 30 questions and see how their position changes. Note that in this interaction, the positions of the parties remain unchanged.

Data. To build the metaphoric map we utilize the data collected by Kieskompas [2] during the Dutch General Elections of 2021. The dataset [11] contains 37,083 user *positions* after filtering out repetitive and incomplete responses, unrealistically short response times (threshold of 1,800 seconds – 60 seconds per question)) and leaving in only PC or laptop users. A single user's *position* consists of responses on a five-point Likert scale from fully disagree to fully agree on the 30 political *topics or questions* on varied subjects such as from national security to climate policies (refer to the supplementary material for the exact formulation of questions).

2.2 Participants

Participants[2] were recruited via Prolific[3] in two rounds: March 28-29, 2024 (260 responses), and April 8-10, 2024 (130 responses), totaling 390 participants residing in the Netherlands. After screening for low-effort responses using attention checks, 8 participants were excluded, resulting in a final sample of 382. All were adults and compensated according to Prolific's standard rates. The sample comprised 209 males, 168 females, and 5 who preferred not to disclose gender. Most were under 30; 262 had higher education (bachelor's+), 120 had vocational or no degrees. This aligns with typical VAA users: younger, highly educated. Participants were randomly assigned via Qualtrics to control (n=128), intermediate (n=128), or experimental (n=126) conditions, ensuring balanced groups for valid comparisons.

2.3 Measurements

We used the following measures:

Vote choice was binary coded as *affected* or *unaffected* considering participants' response to "By using the application..." as suggested in Kamoen et al.'s work[17]. If the response was "I was able to determine my preference for a specific political party" or "I started to doubt which political party I prefer", it is coded as *affected*. If it was "Nothing has changed in relation to my preference for political parties." or "My initial preference for a political party has been confirmed.", then, it is coded as *unaffected*. Vote choice is a categorical binary variable denoted by y.

Political knowledge is measured as both *factual* and *perceived* knowledge, since they might not imply each other [17]. For the elicitation of factual knowledge, we follow the methodology of [30]. We have selected three questions from the original survey (questions NLTK21_004, NLTK21_021 and NLTK21_025 in Table 1 in the supplementary material), for which the variance amongst the party answers is the largest (JA21, VVD, CDA, 50Plus, CU, SP and Volt) and asked the participants to guess the parties' answers on the selected questions. The idea is that if the visualization helps the viewer to familiarize themselves with the political space, their knowledge of where parties stand with respect to major questions will increase. The mean number of correct answers per condition are compared through bootstrapping.

The perceived knowledge was measured by asking participants evaluate the following statement on a five-point Likert scale: "By using the application, I gained more understanding of the positions of political parties." Similarly to factual knowledge, bootstrapped mean values for each condition is calculated and visualized with their corresponding confidence intervals.

Opinion strength As part of the experiment we ask users to evaluate on Likert scale 30 political statements that are used in voting advise application Kieskompas to measure the people proximity to parties, refer to Table 1 in the supplementary material. Following Pandey et al. [25], we binary-coded responses to each political

[2]The Ethics and Privacy Quick Scan of the Utrecht University Research Institute of Information and Computing Sciences classified this research as low-risk, and therefore a full ethics review was not required.

[3]https://www.prolific.com/

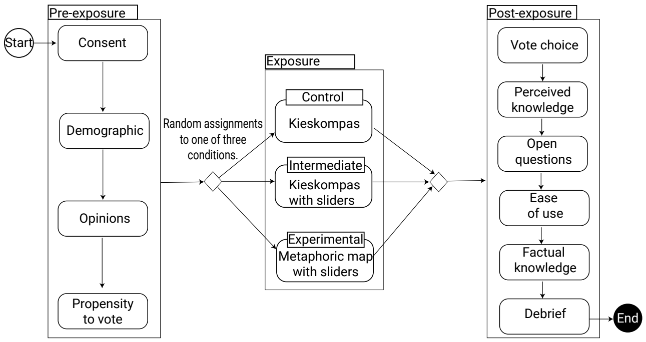

Figure 2: The flow of the experiment.

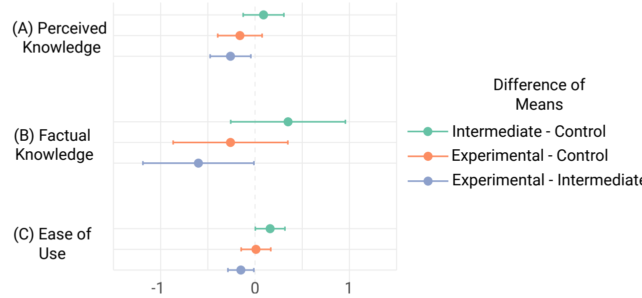

Figure 3: Difference in means with 95% CIs for (A) perceived knowledge, (B) factual knowledge, and (C) ease of use.

statement as strong (fully agree/disagree) or weak (all others). The opinion strength, denoted by o, is an interval variable represented by the number of strong answers.

Propensity to vote (*PTV*) was categorized as *high*, *low* or *non-eligible* based on which of the following statements best reflected the user's voting preference during the previous elections: *high PTV*:"I was sure whom to vote for", *low PTV*: "I was hesitating between few parties" or "I was hesitating between many parties" and *not eligible*: "I did not vote / wasn't allowed to vote". The non-eligible participants were excluded from the analysis. Propensity to vote is therefore a categorical, binary variable denoted by p.

Open question In an open question, the participants were asked to describe how they interpret their position on the graph. We planned to perform an explorative analysis of these data in a manner similar to Bruinsma [7].

Ease of use Ease of use was measured as an indicator of usability, using an adapted version of the Ease of Use scale from the Technology Acceptance Model [8], tailored to the context of VAAs. This scale consists of six statements each evaluated on a five-point Likert scale, ranging from "very unlikely" to "very likely." Participants rated their agreement with statements such as "Learning how to use the application would be easy for me," and "My interaction with the application would be easy and smooth." Higher scores indicate a greater perceived ease of use. Bootstrapped mean values were computed per experimental condition to assess differences in usability perceptions across the designs.

2.4 Procedure

The experiment, refer to Fig. 2, started with informed consent and followed by pre-exposure phase where we collected demographics information, regarding participants age, gender and education level, participants opinions on 30 political statements, and their propensity for vote. Then each participant was randomly assigned to any of three experimental conditions detailed in Sec. 2.1. Participants had unlimited time to explore and interact with the visualizations.. Afterwards, we collected post-exposure data regarding vote choice, perceived political knowledge, asked the open question, ease of use of the VAA and factual political knowledge in this particular order.

3 Results

All results are interpreted by visually comparing 95% confidence intervals [10]. For detailed analyses script, please refer to the supplementary material (analysis.zip) available at the link provided in the abstract.

Vote choice To investigate how experimental condition (c_1, c_2), pre-exposure propensity to vote (p), and political opinion strength (o) influenced participants' likelihood of changing their vote choice (y), a logistic regression model was fitted using 1000 bootstrapped samples. Interaction terms between propensity to vote and visualization condition ($c_1 \times p$ and $c_2 \times p$) were included to assess whether the influence of visualization design depended on user's propensity to vote.

The model coefficients were averaged across 1000 bootstrapped samples particularly in light of class imbalance and the use of synthetic data generated via SMOTE [24]. The coefficients for propensity to vote ($M = -.67$, 95% $CI = [-2.04, 0.7]$), intermediate condition ($M = -.42$, 95% $CI = [-1.34, 0.5]$), and experimental condition ($M = -.40$, 95% $CI = [-1.34, 0.54]$) are slightly negative. However, the confidence intervals largely overlap with zero, although the overlap is smallest for the propensity to vote. This means that participants with high propensity to vote were less likely to change their vote. The coefficients for opinion strength ($M = -.59$, 95% $CI = [-1.59, 0.41]$) and the interaction terms *intermediate × propensity to vote* ($M = .16$, 95% $CI = [-1.66, 1.98]$) and *experimental × propensity to vote* ($M = -.06$, 95% $CI = [-2.14. 2.02]$) are all zero centered. As such, the results show no evidence that vote choice is meaningfully affected, refer to Fig.3 in supplementary material.

Perceived knowledge The mean perceived knowledge per condition, based on 1000 bootstrapped samples, was lowest in the experimental condition ($M = 3.43$, 95% $CI = [3.27, 3.59]$), followed by control ($M = 3.59$, 95% $CI = [3.41, 3.77]$) and intermediate ($M = 3.68$, 95% $CI = [3.54, 3.82]$). As shown in Fig. 3A, there was no evidence of a difference in perceptual political knowledge between the intermediate and control conditions ($M = .09$, 95% $CI = [-0.13, 0.31]$), nor between the experimental and control conditions ($M = -.16$, 95% $CI = [-0.4, 0.08]$). However, we observed some evidence of a difference between the experimental and intermediate conditions, with lower scores for the experimental condition ($M = -.26$, 95% $CI = [-0.48, -0.04]$). These results suggest that the metaphoric map may enhance less perceptual political knowledge compared to the Kieskompas.

Factual knowledge The intermediate condition scores highest on factual knowledge ($M = 6.74$, 95% $CI = [6.33, 7.15]$), followed by the control ($M = 6.39$, 95% $CI = [5.96, 6.82]$) and experimental condition ($M = 6.14$, 95% $CI = [5.69, 6.59]$). A comparison of the differences between conditions (see Fig. 3B) reveals results similar to those for perceived knowledge: there was no evidence of a difference between the intermediate and control conditions ($M = .35$, 95% $CI = [-0.26, 0.96]$), nor between the experimental and control conditions ($M = -.26$, 95% $CI = [-0.87, 0.35]$). In contrast, there was some evidence of a difference between the experimental and intermediate conditions, showing lower scores for the experimental condition ($M = -.60$, 95% $CI = [-1.19, -0.01]$). These findings suggest that the metaphoric map results in lower levels of factual political knowledge compared to the Kieskompas.

Ease of use The answers to the ease of use questions were aggregated by computing the mean per participant and per condition. The intermediate condition had the highest mean ($M = 4.58$, 95% $CI = [4.5, 4.66]$), followed by the experimental condition ($M = 4.43$,

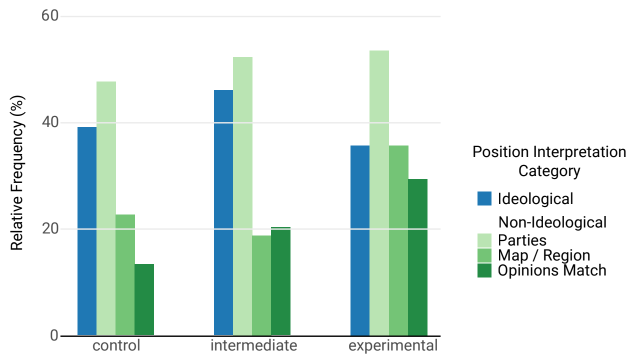

Figure 4: Relative frequency of responses categorized as ideological or non-ideological (*e.g.*, based on political party, map/region, or opinion matching) across the control, intermediate, and experimental conditions.

95% $CI = [4.31,\ 4.55]$), and the control condition ($M = 4.42$, 95% $CI = [4.34,\ 4.5]$).

Comparing the differences (see Fig. 3C), we observed some evidence of a difference between the intermediate and control condition ($M = .16$, 95% $CI = [0,\ 0.32]$) , as well as between the experimental and intermediate condition ($M = .15$,95% $CI = [0.01,\ 0.29]$), with the intermediate condition scoring higher in both comparisons. In contrast, there was no evidence of a difference between the experimental and control conditions ($M = .01$, 95% $CI = [-0.15,\ 0.17]$). These findings suggest that interactive sliders contribute more to ease of use than toggle buttons, while the metaphoric map results in lower ease of use compared to the Kieskompas.

Position on the visualization Here we present the results of the analysis of the answers given in the open question: "How do you interpret your position on the graph?". For more details refer to supplementary material. The answers were coded with the following tags: "ideological" – mention of some ideological position, "parties" – some form of closeness to a party, "map / region" – mention of a location on the map, "opinions match" – mention of values, opinions, answers.

Fig. 4 shows the relative frequency of categories for responses. The blue bars represent subjective and ideological interpretations (tag "ideological"), while the green bars are the categories that can all be understood in terms of non-ideological and more objective interpretations (tags "parties", "map/region", "opinions match").

The results show that the relative distribution of responses in the control and intermediate conditions are similar. On the other hand, in the experimental condition, the ratio of ideological to non-ideological is different when compared to control and intermediate conditions. In particular, the frequency of ideological interpretations is decreased (blue bars) while the relative frequency in all non-ideological interpretations (green bars) is increased. Thus, respondents in the experimental condition more often refer to their position in terms of matching opinions (*e.g.*, position matches their opinion on statements or opinions of parties), regions on the map (left side, red zone), and in relation to parties (close to party A).

4 Discussion and Conclusion

Measuring the influence of the three experimental conditions on vote choice, we found no significant effect. This aligns with earlier findings that VAAs do not strongly affect vote choice [23]. This result may be attributed to the experimental setup, which captures actual change or, as in our case, the user's perception of such change. More fine-grained studies are needed to detect subtler shifts, such as increased certainty or changes in sympathy toward parties.

Results for perceived and factual political knowledge, as well as ease of use, show a clear trend. The MM scored lower on all three compared to the PC. The difference in ease of use can likely be attributed to familiarity: users are more accustomed to axis-based visualizations. Scatterplots, which underlie the metaphoric map, are less commonly encountered and might be harder to interpret without prior exposure. This could explain why, despite offering richer information – including crowd positions and clustering – the metaphoric map appears harder to understand. We speculate that higher levels of visualization literacy are required to effectively read this representation. Moreover, the knowledge-related tasks may not have captured other aspects the MM could support, such as party popularity.

Sliders were rated more intuitive than toggles. However, no evidence of difference was found regarding political knowledge. Since sliders allow for rapid adjustment and immediate feedback on positional changes, one might expect improved understanding. The absence of such an effect could imply that users rely more on prior knowledge than interaction when judging party positions. Alternatively, our experimental design may not have fully captured the benefits of slider-based interaction. Measuring knowledge before and after exposure might reveal clearer effects.

In analyzing responses to the open-ended question, we observed that users in the experimental condition were more likely to interpret their position in non-ideological terms – such as spatial proximity to parties or clusters of similar opinions – compared to users in the other conditions, who more frequently referenced ideological labels. This shift suggests that MM may encourage more objective interpretations, possibly due to the absence of ideological axes. However, this conclusion is based on informal inspection. A more systematic analysis would be needed to confirm these observations and to understand how users interpret such representations across a broader range of political contexts.

To our knowledge, this is the first controlled study that directly compares MM to a traditional PC design in the context of VAAs. In particular, we suggested to use a dimension reduction technique for displaying parties and voters opinions in a VAA. This includes using data-driven distances between points (parties, voters) in contrast to showing only the parties positions according to only two ideological pre-determined axes. While findings show no impact on vote choice, they reveal important trade-offs in usability and interpretability – providing design insights for future VAA tools.

However, several limitations should be noted. First, the study relied on short-term exposure and self-reported measures, which may not capture longer-term or behavioral effects. Second, the MM condition included crowd data – social information – that was not present in the other conditions, which could confound the effect of visual encoding alone. Additionally, participants may have found the MM less intuitive due to lower familiarity with MMs in this context. Despite offering richer representations, such designs may require higher visualization literacy—raising questions about whether these effects persist or diminish with repeated exposure or training. Future work could isolate specific variables—for instance, by adding crowd data to PC or remove it from MM — to more precisely assess their individual impact. This also raises broader questions about accessibility and inclusivity in political interfaces: can such tools serve a diverse electorate if they require a certain level of visual or data literacy? Last, but not least, the study was not conducted in run-up to some election, so the ecological validity may have been limited.

Conclusion The MM encourages more objective political interpretations but compromises usability and knowledge. These findings suggest that future designs may benefit from improved user guidance or hybrid visualizations that balance usability with the interpretive depth offered by data-driven representations. Adding clear explanations or interactive help could make such visualizations easier to understand without losing their richness.

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