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Visual preferences in map label placement

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Abstract
Digital maps are important for many decision-making tasks that require situational awareness, navigation, or location-specific data. Often, digital mapping tools must generate a map that displays labels near associated features in a visually appealing manner, without occluding important information. Automated label placement systems generally accomplish this nontrivial task through a combination of heuristic algorithms and cartography rules, but the resulting maps often do not reflect the preferences and needs of the map user. To achieve higher quality map views, research is needed to identify cognitive and computational approaches for generating high-quality maps that meet user needs and expectations. In this paper, we present a study that explores the visual preferences of map users and supports the development of a preference model for digital map displays. In particular, we found that participants demonstrated consistent preferences for how labels are placed near their point of interest, and that they were more likely to choose positions that prioritized alignment over distance when ranking labels that made trade-offs between them.

1 Introduction

Digital maps are commonly used to plan routes and navigate, such as by car on a street map or by plane on aeronautical charts. Other uses include visualizing and understanding spatial features or making decisions about how to deploy resources in a geographic area. In such scenarios, maps must display large amounts of relevant spatial information to the user in an intuitive display that helps them find the needed information quickly and easily.

For centuries, cartographers conducted the time-consuming task of designing detailed maps and, in the process, created many best practices and standards to represent geographic information accurately, while supporting spatial processing and reducing clutter [1]. However, modern digital maps offer functionality that is not available in print maps, such as panning, scaling, and adding or removing layers. This complex environment makes it impossible to manually create map views for every scenario [2]. Mapmakers have turned to algorithmic and machine learning approaches [3, 4] to support generating digital map displays.

Label placement algorithms seek to place labels near their respective features in such a way as to minimize collisions between map features and to reduce clutter. Several automated and interactive generalization techniques have been incorporated in map making pipelines to reduce the amount of manual work that is required [5, 6]. However it is difficult to codify every scale and view and as the complexity of a map increases, the resulting layouts often do not meet the standards set forth by cartographers [7]. Although much work has focused on improving map generalization tools and conducting user studies to validate a variety of tradeoffs and decisions in digital map interfaces, additional research is

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needed to examine how user preferences can be included in the design of map displays. Such information could lead to higher quality layouts that adapt to individual users [8].

In this paper, we present a study that explores the label placement preferences of map users. We show that people exhibit consistent visual preferences about where labels should be placed in relation to points of interest on a map. In particular, we examine user preferences for a label's alignment with a point and its distance from a point. We also introduce a preference model of label placements that tradeoff between these two attributes.

2 Related work

Map label placement is one of the most challenging processes in map creation. To be useful, the labels must be placed near their associated features in a readable way, without colliding with or obscuring other labels [9]. Even in their simplest form, label placement algorithms are computationally complex, falling into the class of NP-complete algorithms [10], where the time required to find an optimal layout increases exponentially as the number of label placements increase. This means that optimal label placements cannot always be found, and label placement engines must instead use heuristics to seek to find optimal placements but do not guarantee an optimal solution [11]. Digital maps make the problem even more complex, requiring optimal placements to be recalculated as the map is scaled or layers are added and removed. Recent work has introduced new metaheuristics that identify promising regions in the search space to explore in more detail [12], or augmented existing heuristics with data mining spatial features of label placements [13].

Research in human factors and user experience has explored how different types of users may interact and understand maps differently. For example, Ooms et al. [14] explored the differences in novice and expert users in recalling details about spatial maps, while Palka et al. [15] considered how different stakeholders read disaster evacuation maps. Dudley et al. [16] used Bayesian optimization to refine the design of informational tooltips based on crowdsourced user performance data.

Since users can have difference uses and needs for a maps, it is expected that their individual preferences could improve a map display. Preference researchers have explored many computational methods to represent and learn preferences [17, 18], and some work has considered incorporating preferences into maps and to recommend content based on location. For example, Opperman & Specht [19] aimed to deduce the context of where and how a map is being used to provide information that a user would want in that context. Stiller et al. [20] considered information such as how far a user had travelled, to deduce a user's preferences for certain places and provide better recommendations. Other work by Mac Aoidh et al. [21] collected interaction behavior, such as mouse movements, to determine user interests so that map content could be filtered to only show information the user would not be interested in.

To our knowledge, previous work has not explored representing people's explicit preferences for label placements on digital maps. The study presented here describes an initial effort to understand people's visual preferences for label placement, particularly considering the alignment and distance of a label from its point of interest. Additionally, the data collected from the study is used to design a model of tradeoffs between competing preferences. This work provides a first step towards designing models that can support automated label placement algorithms in generating displays based on user preference.

3 Methods

We conducted a study of visual preferences for map displays to better understand people's label placement preferences. It examined what type of label positions people prefer with regards to the distance and alignment attributes of label placements. We also surveyed participant preferences when trading off between conflicting attributes. Using the resulting dataset, we modeled the tradeoffs people made when choosing between labels that differed along competing dimensions and showed that individuals expressed consistent preferences when considering the alignment and distance of a label from its point of interest.

Participants: A total of 478 students from Louisiana State University (LSU) participated in the study for course credit. The study was approved by the LSU IRB. All participants self-reported that they had vision that was normal or corrected to normal, and 3 participants stated that they were colorblind. Participants were asked how often they use maps in their daily life (9.4% rarely/never, 35.3% a few times per month, 40.0% a few times per week, and 15.3% daily). They were also asked which digital map applications they have experience with (Google Maps—83.5%, Apple Maps—76.8%,

Fig. 1 Map backgrounds used in the survey. **A** Example of a simple background. **B** Example of a complex background

Waze—63.6%, Map My Run—7.8%, MapQuest—4.8%, Strava—2.9%, All Trails—2.5%, Other—3.1%). Participants were presented with four separate tasks at the time of completion. The first three tasks focused on the participants' preferences based on the various map layouts that were presented. The tasks considered the following preference scenarios: 1: route label preferences, 2: point label preferences, 3: point label preference tradeoffs and 4: making decisions given a fictional boss' preferences. In this paper, we consider point label preferences (tasks 2 and 3) specifically and tasks 1 and 4 are not discussed here.

4 Point label preferences

Materials: The point label preferences task was a within subjects design with three independent variables: alignment (top left, direct left, and bottom left), distance (close, medium, and far), and background (simple map and complex map). This resulted in two separate 3×2 repeated measures designs: alignment by background and distance by background. The dependent variables included preference (binary choice) and preference strength (scale from 0 to 100).

Two map backgrounds were taken from Mapbox.[1] The original labels were removed using a custom stylesheet for the map, and then new street and point labels were added using an image editor[2] to produce the 9 simple and 9 complex maps (see Fig. 1 for examples of simple and complex maps). Each map had three points placed representing the gym, post office, and shopping mall. Points were labeled with the appropriate text and a leader line to the point that the label was associated with. The maps differed based on the alignment and distance conditions.

Multiple label placement recommendations have been proposed by the literature [22, 23] and applied by default in tools such as QGIS.[3] Since the focus of this research was to establish whether people demonstrate any preferences for label placements that could be modeled, the selection of specific placements in each condition was less critical to the study's overall conclusions. To create the alignment condition, the distance between the label and the point was held constant at the medium distance. The labels appeared at one of three possible locations: top left, direct left, or bottom left. The alignment condition had a total of 3 maps. To create the distance condition, the label alignment was held constant at the top left alignment. The label appeared at the top left alignment at one of three possible distances from the point: close (8 pixels from the point), medium (25 pixels from the point), and far (35 pixels from the point). The distance condition had a total of 3 maps.

All stimuli and questions were entered into Qualtrics online survey program. The study was divided into 4 blocks including 2 alignment blocks and 2 distance blocks. Each block compared each of the three placements for a total of 3 comparisons per block. Map backgrounds were consistent within a block, with participants seeing the comparisons on

[1] Mapbox.com.
[2] Gimp.org.
[3] Qgis.org.

Fig. 2 Example comparison trial from the Point Label Preferences task in the survey. Alignment for both maps is fixed to top left. Distance is manipulated between the two maps, with labels on the left map positioned close to their point of interest, while those on the right are positioned farther away

the complex background in 2 blocks and on simple background in the other 2 blocks. Participants were presented with the blocks in the following order: alignment on simple background, distance block on simple background, alignment block on complex background, and distance on complex background. The comparison trial order in each block was randomized and the map location on the screen was randomized in each trial. Figure 2 shows an example comparison trial from the study.

Procedures: Participants became aware of the study through the LSU psychology department's participant recruitment system (SONA) and were informed they would receive course credit for completing it. Once participants signed-up for the study they were provided a link to complete the study through Qualtrics. After participants consented to participate, the instructions were presented. The participants' objective was to choose the preferred map between the two presented. For example, a map on the left might show the gym label at the top left alignment with medium distance and the right might show the gym label at the direct left alignment with medium distance. All remaining points on the map would have the same alignment and distance. For the alignment condition the participant would be choosing their preference between the top left and direct left on this trial. A trial for the distance preference was the same except the manipulated feature was label distance and constants was alignment. Following the choice of preferred map, a slider bar would appear with 0 to 100 and participants would rate how strongly they preferred the map with 100 indicating strongly preferred. Participants completed 6 trials for the alignment condition and 6 trials for the distance condition for a total of 12 trials.

Results: A Chi-square goodness of fit test was used to understand whether or not participants had label placement preferences. If participants had no preference, then their responses should be evenly distributed between the two choices in each comparison. The following paragraphs report on participants' choices and the goodness of fit results for alignment placements on simple and complex backgrounds, followed by the results for distance on simple and complex backgrounds.

When considering the alignment preferences on the simple background, recall that people were asked to choose between label placements aligned to Top Left and Bottom Left, Bottom Left and Left, and Top Left and Left. Evidence was found to support participants having a preference when shown Top Left and Bottom Left, compared to having no preference, $X^2 = 8.04, (1, N = 478), p = .005$. In this binary choice question, 270 (56.5%) of people chose Top Left over Bottom Left. Participants differed in their alignment choice, but when examining the strength of their preference, Top Left ($M = 51.57$) and Bottom Left ($M = 50.32$) did not differ, $t(476) = 0.46, p = .647, \text{Cohen's}\,d = .04$. Compared to having no preference, support was found for people having a preference when choosing between Bottom Left and Left, $X^2 = 57.65, (1, N = 478), p < .001$. In this choice, more people chose Left, 322 (67.4%). The choice of Left ($M = 53.40$) was not accompanied with a higher strength of preference rating than the choice of Bottom Left ($M = 48.35$), $t(476) = 1.77, p = .077, \text{Cohen's}\,d = -0.17$. Finally, evidence was found to support a preference over having no preference when Top Left and Left were presented, $X^2 = 29.13, (1, N = 478), p < .001$, with 298 (62.3%) participants choosing Left more than Top Left. As with the previous alignment choices on simple backgrounds, though the number of observations supported a preference, how strongly the participants felt about their preference did not differ between Top Left ($M = 50.34$) and Left ($M = 52.66$), $t(476) = -0.87, p = .384, \text{Cohen's}\,d = -.08$.

Following our analysis of the alignment preferences on the simple background, we analyzed the alignment preferences on the complex background. Similar to the choices made on the simple background, participants were asked to choose between label placements aligned to Top Left and Bottom Left, Bottom Left and Left, and Top Left and Left. Evidence was found to support participants having a preference when shown Top Left and Bottom Left, compared to having no preference, $X^2 = 15.473, (1, N = 478), p < .001$. In this binary choice question, 282 (60.0%) of people chose Top Left over Bottom Left. The choice of Top Left ($M = 48.95$) was not accompanied by a higher strength of preference rating compared to the choice of Bottom Left ($M = 49.85$), $t(476) = -.32, p = .750, \text{Cohen's}d = -.03$. Compared to having no preference, support was found for people having a preference when choosing between Bottom Left and Left, $X^2 = 45.824, (1, N = 478), p < .001$. In this choice, more people chose Left, 313 (65.5%). A higher preference rating was observed for the choice of Left ($M = 54.41$) compared to the choice of Bottom Left ($M = 45.75$), $t(476) = -2.96, p = .003, \text{Cohen's}d = -.29$. Finally, we considered when people made the choice between Top Left and Left on the complex background. In this scenario, no evidence was found to support a preference over having no preference, $X^2 = 1.883, (1, N = 478), p = 0.170$, with 254 (53.1%) of participants choosing Left placements over Top Left. However, when considering the choice between Top Left ($M = 46.07$) and Left ($M = 53.53$) on the complex background, a stronger preference strength rating was found for Left, $t(476) = -2.6, p = .008, \text{Cohen's}d = -.25$.

Next we considered the distance preferences on the simple background where people were asked to choose between label placements that, relative to their points of interest, were located at a Close and Medium distance, Far and Medium distance, and Close and Far distance. We first considered the choice between Close and Medium distances and found evidence for participants having a preference when compared to having no preference, $X^2 = 29.26, (1, N = 478), p < .001$. In this choice, 344 (72.0%) of people chose the map with labels placed at a Medium distance over those placed at a Close distance. The choice of Medium distance ($M = 53.35$) was accompanied by a higher strength of preference rating than the choice of Close ($M = 46.87$), $t(476) = -2.17, p = .031, \text{Cohen's}d = -.22$. When Far and Medium distanced labels were presented, we found support for a preference compared to no preference, $X^2 = 29.13, (1, N = 478), p < .001$. In this scenario, 298 (62.3%) of participants chose Medium distanced labels. Participants differed in their alignment choice, but when examining the strength of their preference, Far ($M = 48.38$) and Medium ($M = 47.67$) did not differ, $t(476) = -.25, p = .801, \text{Cohen's}d = -.02$. Finally, when Close and Far distances were considered, evidence was found to support a preference compared to no preference, $X^2 = 108.85, (1, N = 478), p < .001$, with 352 (73.6%) of people choosing Far labels. In addition to finding support for a preference, the choice of Far ($M = 51.76$) was accompanied by a higher strength rating compared to Close ($M = 43.65$), $t(476) = -2.70, p = .007, \text{Cohen's}d = -.28$.

Finally, we analyzed the distance preferences on the complex background, considering the choices made between labels placed at a Close and Medium distance, Far and Medium distance, and Close and Far distance. We considered the choice between Close and Medium distances and found evidence for participants having a preference when compared to having no preference, $X^2 = 134.97, (1, N = 478), p < .001$. In this choice, 366 (76.6%) of people chose the map with labels placed at a Medium distance over those placed at a Close distance. A higher preference strength rating when choosing Medium ($M = 52.10$) compared to when choosing Close ($M = 44.28$), $t(476) = -2.46, p = .014, \text{Cohen's}d = -.22$. When we considered when people made the choice between Far and Medium distance placements, we found support for people having a preference compared to no preference, $X^2 = 42.18, (1, N = 478), p < .001$. In this scenario, 310 (64.9%) of people chose the Medium distance placement over the Far distance. When making the choice between Medium and Far, people did not choose higher preference strength ratings after choosing Medium ($M = 42.48$) or Far ($M = 42.15$), $t(476) = .11, p = .911, \text{Cohen's}d = .01$. Finally, when Close and Far distances were considered, evidence was found to support a preference compared to no preference, $X^2 = 48.34, (1, N = 478), p < .001$, with 315 (65.9%) of people choosing Far labels. For the participants making this choice, we found that there was a higher preference strength rating for those choosing Far ($M = 52.21$) compared to those choosing Close ($M = 46.34$), $t(476) = -2.02, p = .04, \text{Cohen's}d = -.20$.

Discussion: In summary, when choosing between placements on both the simple and complex background, we found that people exhibited a preference for label placements when compared to having no preference. More people chose labels placed at a Medium distance compared to both Far and Close positions, and chose Far positions more often than Close. For alignment choices on the simple and complex backgrounds, more participants chose labels placed on the Left compared to both Bottom Left and Top Left, and chose Top Left more often than Bottom Left. However, in the comparison between Top Left and Left on the complex background, the difference between those choosing Top Left and Left was not significant compared to the expected distribution when participants have no preference. This seems to indicate that in most scenarios considered, our participants tended to choose a particular a label placement over others. In the next section we explore participants' choices when they are forced to make a

Table 1 Each tuple in the label set represents a tradeoff in preferences on a single map

Label Set 1	(Top Left, Medium), (Direct Left, Far), (Bottom Left, Close)
Label Set 2	(Top Left, Far), (Direct Left, Close), (Bottom Left, Medium)

Participants were asked to rank the maps in a given set from most preferred to least preferred

tradeoff between alignment and distance, and use the collected dataset to model preference tradeoffs and explore how consistent individuals were in selecting label placements based on alignment and distance.

5 Point label preference tradeoffs

Materials: The goal of the point label preference tradeoff task was to collect data about how people rank label placements that change in both distance and alignment. The resulting dataset was then used to fit a model of label placements that represented the overall preference as a function of the distance and alignment preferences collected in the previous task.

To collect preference data that could be used to fit the preference model, participants were surveyed about their preferences using a preference ranking (1–3) of maps that represented various tradeoffs between alignment and distance. Rankings were collected here as a potential additional information to consider when developing the model and for the purpose of this analysis, first ranked placements are treated as the preferred choice. Participants performed their rankings on two separate label placement map sets. A change from the previous task included increasing the number of map backgrounds to increase the number of data points collected for each label placement set from 2 to 4. This resulted in 8 total tradeoff rankings per individual (4 in Label Set 1 and 4 in Label Set 2), providing additional data for fitting the model. Each set of maps included two simple backgrounds and two complex backgrounds. These new map backgrounds were taken from Mapbox and added to the two map backgrounds from the previous task. GIMP was again used to create new maps by adding the 3 point labels (gym, post office, shopping mall) to each of the backgrounds. One map was created for each of the placement options in Label Set 1 and 2. This resulted in 24 total maps, 3 maps in each of the 2 label sets on 4 backgrounds.

A label placement set consisted of three maps, each representing a different tradeoff between alignment and distance. Between the two label placement sets six possible combinations were surveyed. The participants ranked maps from each set described in Table 1.

The label sets in Table 1 only represent a subset of the combinations that could be created from all possible alignments and distances. The chosen label sets was limited to 2 to ensure that participants could complete both parts within the same session. Since the focus of this work was to establish whether label placements preferences could be modeled, we focused on label sets involving the same alignment and distance positions explored in the previous study. All stimuli and questions were entered into Qualtrics online survey program. The study was divided into 4 blocks, one for each background, starting with the two complex backgrounds and proceeding to the simple backgrounds. Each block included two questions that displayed each of the maps in the label placement set, using the background for that block. Participants were asked to rank the maps from most preferred (#1) to least preferred (#3). The order of the label placement sets in each block were randomized, and the map location on the screen was randomized in each question.

Procedures: After completing the point label preferences task, participants were presented with the instructions for the point label preferences tradeoff task and then proceeded through each of the questions. The participants' objective in this task was to rank the three maps from a label placement set from the most preferred to the least preferred. In each question, participants were presented with 3 maps sharing the same background, but differing in label placement. For example, if Label Placement Set 1 on the simple map 1 was being considered, the participants would see a vertical list of maps using the simple map 1 background. Each map would have all point labels placed at either the (Top Left, Medium), (Direct Left, Far) or (Bottom Left, Close) locations. Next to each map were radio buttons that could be selected to specify 1st, 2nd, or 3rd place. Participants were required to choose a unique ranking for each map. After making their selections, they proceeded to the next question.

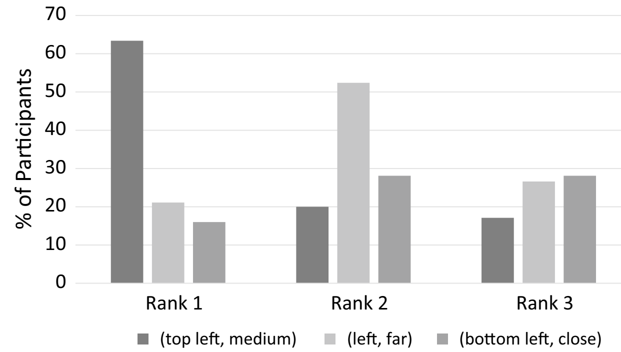


Fig. 3 Rankings of label positions in Label Set 1

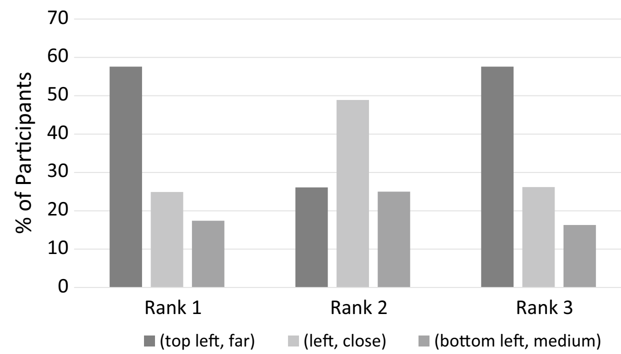


Fig. 4 Rankings of label positions in Label Set 2

Results: When considering Label Set 1 (see Fig. 3), we note that participants ranked (Top left, Medium) more often in first place (63.4%), while (Bottom Left, Close) is more often ranked in last place (56.4%). In Label Set 2 (see Fig. 4), we see that more people ranked (Top Left, Far) first (57.6%), while ranking (Bottom Left, Medium) third (57.6%).

A visualization of the options that the participants ranked first in Label Set 1 and Label Set 2 can be seen in Fig. 4. This can help us better understand how participants ranked choices with competing attributes. We found that most of the participants appeared to prioritize alignment over distance information in both scenarios. As a group, most of the participants (Label Set 1: 63.4%, Label Set 2: 57.6%) ranked first the labels placed at the (Top Left, Medium) position. 74.8% of those who chose the top left label in Label Set 1, chose the (Top Left, Far) label position in Label Set 2. Of those who ranked (Left, Far) in first place for Label Set 1, 33.8% continued to rank the left position (Left, Close) first. Finally, of those who ranked (Bottom Left, Close) first, 41.4% continued to rank the Bottom Left position first in Label Set 2.

We further observed that few participants prioritized distance when ranking based on tradeoffs. Only a minority of those who preferred a label at a particular distance position in Label Set 1 went on to prefer it in Label Set 2. For example, of those who ranked first (Top Left, Medium) in Label Set 1, only 7.2% preferred (Bottom Left, Medium) in Label Set 2. Likewise, of those who preferred (Left, Far), 33.3% went on to rank (Top Left, Far) first in Label Set 2. Of those ranking (Bottom Left, Close) first in Label Set 1, 33.0% went on to rank (Left, Close) first in Label Set 2.

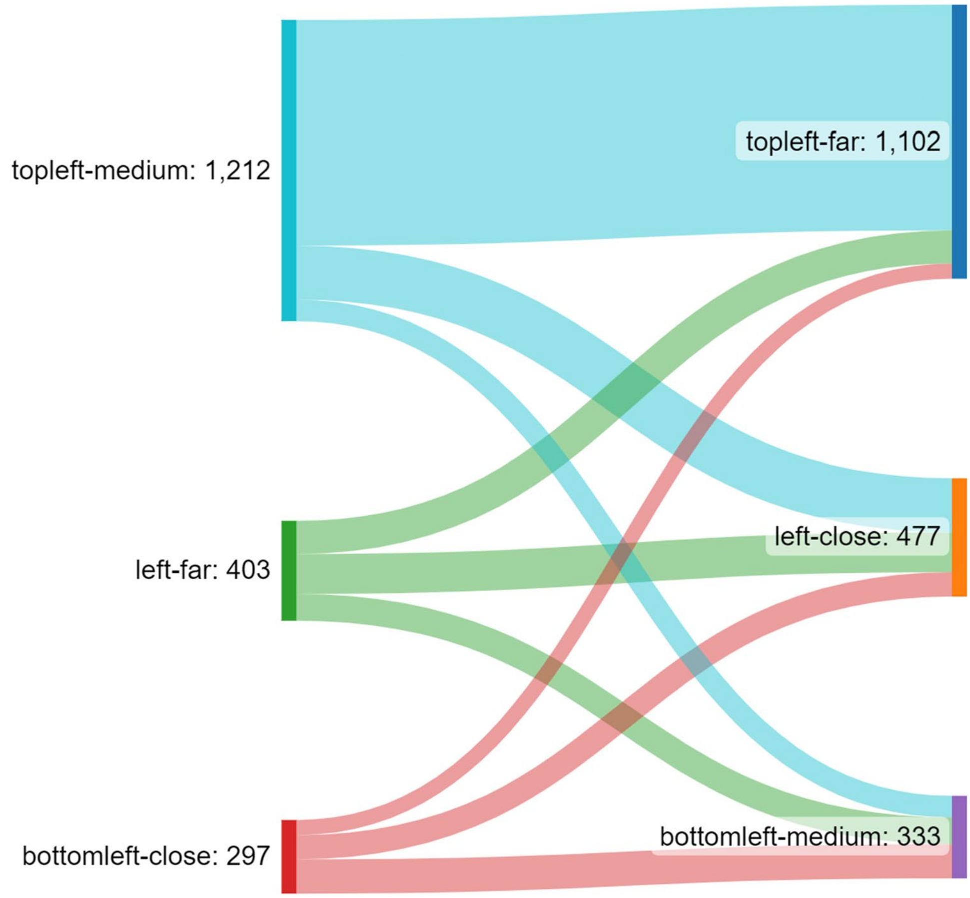
Discussion: When comparing these results with those from the point label preferences task, we found that when the most popular distance position (Medium) was paired with a least popular alignment (Bottom Left), few participants chose to rank (Bottom Left, Medium) highly. Instead, most people chose either (Top left, Far) and (Left, Close). This seems to indicate that more people weighted alignment more highly than distance when ranking between positions that change in both alignment and distance.

5.1 Modeling map preference trade-offs

To better understand how consistent participants were in choosing which label positions to rank first, we employed an additive weights model to estimate each participant's utility for the different label positions in the point label preferences task, and fit it to the collected preference tradeoff data.

In the point label preferences task, participants chose their preferred position between three distance positions and three alignment positions in a series of pairwise comparisons. Using this information, we can generate an order over

Fig. 5 Proportions of participants' first ranked items in Label Set 1 (left) and Label Set 2 (right)



the positions in $A = \{\text{topleft}, \text{left}, \text{bottomleft}\}$ and positions in $D = \{\text{close}, \text{medium}, \text{far}\}$, for each map background, such that $a_1 \geq a_2 \geq a_3$ and $d_1 \geq d_2 \geq d_3$.

We assign a utility to each position, assuming that the relationship between them is linear, and that higher ranked items should have a higher utility than lower ranked items. More formally, n is the number of options compared ($n = 3$ in this case), and $r(x)$ returns a value in $\{1, 2, \ldots, n\}$ that corresponds to the rank index of x. Note that it was possible for multiple positions to share the same rank $r(x)$ if the participant was indifferent between them. Therefore, the utility of the alignment position is $\forall a \in A, u(a) = n - r(a)$, and the utility value of the distance position can then be described $\forall d \in D, u(d) = n - r(d)$

Given these utilities, we can model the rank 1 responses by aggregating the alignment and distance utilities for the label position, as a weighted sum:$u(P) = w_A u\left(a_P\right) + w_D u(d_P)$. Here,$w_A$ and w_D represent the weights applied to the alignment and distance features, respectively.

The weights represent how consistently an individual chose options using a preferred placement found in the point label preferences task. For example, if w_D was closer to 1, then the participant's decisions in the tradeoff task were more consistent with their distance preferences collected in the previous task. If a weight was closer to – 1, then their preferred choices in the tradeoff task were not heavily influenced by their preferences in the previous task.

After the utilities for each option have been generated, the model returns the choice with the highest utility as the preferred option. If multiple choices are tied for the highest utility, then the model is indifferent between them and returns one randomly chosen from a uniform distribution.

As seen in Fig. 5, participants exhibited a variety of strategies when ranking positions, so we model the preference weights for each individual, rather than for the entire group.

Model Rankings: To model a participant's rankings, we use a simple grid search to fit the values for w_A and w_D, chosen between -1 and 1 in increments of 0.1 [– 1, – 0.9, …, 0, 0.1 …, 0.8, 0.9]. We fit the values by selecting the pair (w_A, w_D) that most often resulted in an individual's Rank 1 response over eight total responses (one response for each of the four map backgrounds combined with the distance and alignment preferences gathered in the point label preferences task). The

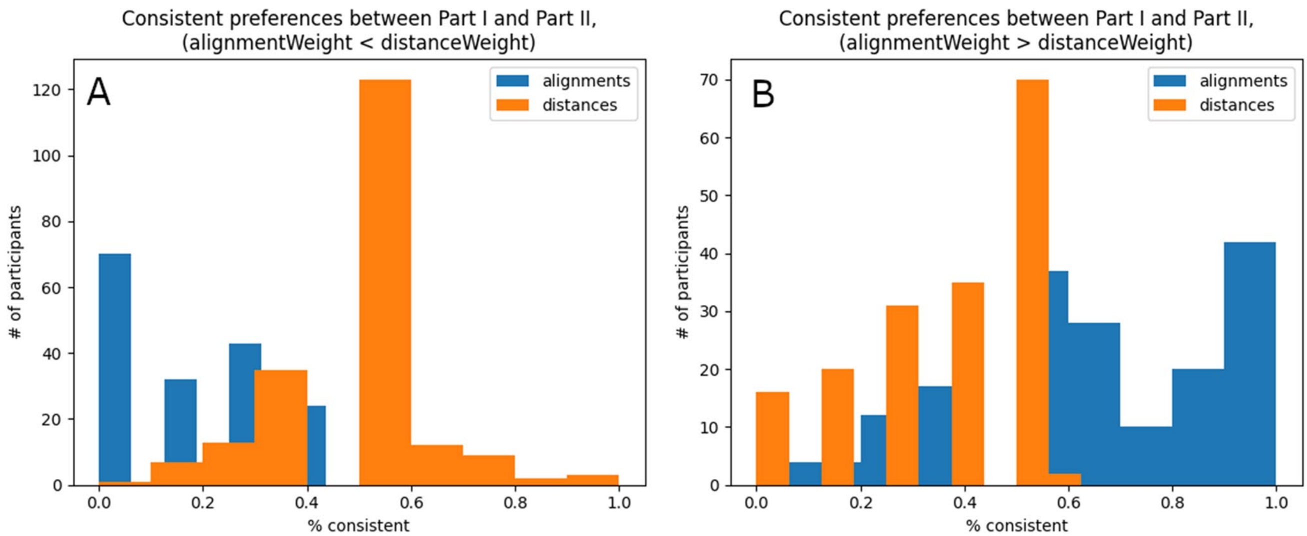


Fig. 6 Consistent Alignment Preferences between the Point Label Preferences and Tradeoffs Tasks in the Survey. A represents the number of participant responses indicating that alignment was weighted lower than distance. B represents the number of participant responses indicating that alignment was weighted higher than distance. If % consistent is 1.0, the participant chose the tradeoff option in every question that aligned with their point label alignment preferences in the previous task

modeled rankings were generated by calculating the utility of the position using the process described above. Since the model broke ties randomly, a variety of outcomes were possible. To ensure that the model works well across a number of different random seeds, we ran the model 20 times. When comparing the runs, there was no statistical difference between them, and the model accurately produced 70.7% (sd = 0.01) of the Rank 1 responses on average. We used one of these runs (accuracy = 70.1%) to perform the weight analysis below.

Weights Analysis: We can analyze the weights of the resulting models to understand how consistent participants were in their preference choices between the point label preferences and point label preference tradeoff tasks in the survey. For example, as seen in Fig. 6, for those participant models where alignment weights were higher than distance weights, $w_A > w_D$ (N = 1392), the participants were generally more consistent in choosing the option that reflected their alignment preferences from the point label preferences task, compared to distance preferences. Likewise, for the participants modeled with alignment weights that were less than distance weights, $w_A < w_D$ (N = 1640), few exhibited weights higher than 0.6, meaning that they were overall less consistent in choosing the option that reflected their distance preferences in the point label preferences task. This supports what we observed in Fig. 5, with more participants prioritizing alignment over distance in the preference tradeoffs.

6 Conclusions and future work

We have introduced a study of visual preferences for the placement of labels on map displays. This study considered whether people have consistent preferences about the alignment and distance of labels from their associated point of interest. We considered preferences when alignment and distance are manipulated independently and together. In general, we found that people preferred specific label positions and that they were more consistent in choosing positions that prioritized alignment over distance.

This work provides an example of how people's visual preferences for digital map displays can be represented using an additive utility model. Such a model could be used to inform a label placement algorithm about user preferences. Going forward, it will also be important to understand how the label placements affect user performance. Future work will investigate how people's performance is affected by different label placements, and whether or not preferred label placements correlate with performance in tasks such as route finding and visual search. Additional work will also investigate how cognitive and spatial information such as saliency, clutter perception scores, color density, and spatial distribution can affect preferences and performance in map displays.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by JS and JLH. The first draft of the manuscript was written by JS. and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability All data and materials can be found at: https://osf.io/fhbjt/

Declarations

Ethics approval consent to participate This data was collected through a study approved by LSU's Institutional Review Board. Prior to their involvement, all participants were provided with informed consent, which included clear information about the study's purpose, procedures, potential risks and benefits. Participants were assured of their right to withdraw from the study at any time. Confidentiality and anonymity of the participants' personal information were maintained throughout the study, and the dataset was de-identified prior to being shared.

Informed consent Informed consent was obtained from all individual participants included in the study.

Competing interests Authors declare that they have no competing interests.

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