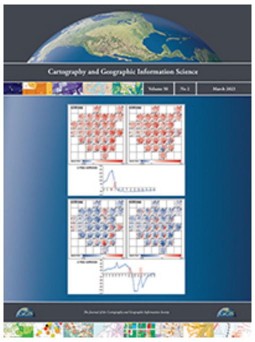

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Assessing the cognition of movement trajectory visualizations: interpreting speed and direction

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ABSTRACT
This paper evaluates cognitively plausible geovisualization techniques for mapping movement data. With the widespread increase in the availability and quality of space-time data capturing movement trajectories of individuals, meaningful representations are needed to properly visualize and communicate trajectory data and complex movement patterns using geographic displays. Many visualization and visual analytics approaches have been proposed to map movement trajectories (e.g. space-time paths, animations, trajectory lines, etc.). However, little is known about how effective these complex visualizations are in capturing important aspects of movement data. Given the complexity of movement data which involves space, time, and context dimensions, it is essential to evaluate the communicative efficiency and efficacy of various visualization forms in helping people understand movement data. This study assesses the effectiveness of static and dynamic movement displays as well as visual variables in communicating movement parameters along trajectories, such as speed and direction. To do so, a web-based survey is conducted to evaluate the understanding of movement visualizations by a nonspecialist audience. This and future studies contribute fundamental insights into the cognition of movement visualizations and inspire new methods for the empirical evaluation of geovisualizations.

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Cognitive evaluation; user evaluation; spatial cognition; movement visualization; movement trajectories; cartography

1. Introduction

Cartographic visualizations have long been used to communicate spatiotemporal information across many domains of knowledge to both practitioners and the public. The origin and history of cartography show that it has, from the beginning, blended the art and science of representing and mapping the world. It is essential, therefore, to know how maps communicate meaning to the viewer through the symbolic representation of information (Montello et al., 2018). Cartographic representation plays an important role in the graphical display of spatiotemporal information (Fairbairn et al., 2001).

Such visualizations, like maps and network diagrams, are increasingly involved in data exploration and analysis of complex behavior in the fields of movement ecology and human mobility science (Demšar et al., 2015; Yuan & Raubal, 2012), as movement is necessarily spatiotemporal. Movement data is collected through various means, including the tracking of individuals using location-aware technologies (LATs) such as Global Positioning Systems (GPS), bio-loggers, radar sensors, and geo-tags in the form of trajectories (i.e. sequence of locations over time). These data, especially if geo-enriched with behavioral and environmental variable, pose complex challenges in the interpretation of patterns that they capture with relation to real-world movement behavior of individuals. The evaluation of movement visualizations is also relevant in the depiction of large-scale directional movement or flows, such as for aggregated movement trajectories (Graser et al., 2020), or in other application areas as ocean currents and wind patterns (Dong et al., 2018; Fukaya & Misue, 2018). Therefore, it is critical to systematically assess the components of visual information design for cognitively plausible mapping of trajectory data and effective communication of movement information.

The field of movement visualization has not always focused on empirical evaluation of how people cognitively *interpret* such map displays (Davies et al., 2015), though there is certainly a need and opportunity (Roth, 2017). Fabrikant has called for a "cognitively inspired and perceptually salient" approach to cartographic displays and has done much work on empirically evaluating map displays for the interpretation of spatial and spatiotemporal data, such as in the case of weather maps (Fabrikant et al., 2010). Cognitive evaluation (similarly referred to as *perceptual evaluation*; Ware, 2013a) poses

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a key opportunity to learn how to support efficient visual communication of complex spatiotemporal information for applied research and decision-making, such as in movement visualization (Lautenschütz, 2012).

Although spatiotemporal displays are critically important to public communication and are widely used in the reporting of both human and animal movement as well as natural phenomena, the creation of such visualizations is guided mainly by general aesthetic principles and design conventions (Dodge & Noi, 2021). In contemporary times, technology may even be "outpacing" cartographic theory for mapping movement and its patterns (Harrower & Fabrikant, 2008). There is certainly a need for a deeper understanding of how users understand time and essential movement parameters (e.g. speed and direction) using spatiotemporal visualizations. This can inform the design of the next generation of geographic displays of movement phenomena, rather than representing movement in a provisional way.

This paper presents an empirical study to evaluate aspects of the proposed cartographic framework for movement in Dodge and Noi (2021). The main goal is to evaluate how different visualization forms impact the cognitive evaluation of movement parameters in geovisualization. The focus is on two-dimensional trajectory maps represented using static and dynamic displays. The study contributes to the understanding of how people interpret movement parameters visualized through trajectories on these types of map displays. Specifically, the main contributions of this study are twofold: (1) Identify and assess a set of Bertin (1983)'s visual variables to properly encode and map movement trajectories and changes in primitive movement parameters such as speed, acceleration, and direction (Dodge et al., 2008). (2) Conduct a web-based survey to evaluate the efficacy of various visual variables in capturing movement parameters using static and dynamic displays. The outcome of this research has implications not only for the design of digital map resources and geographic visualizations, such as for digital navigation aids, but also for understanding real-time human comprehension of the visual information display of spatiotemporal phenomena.

2. Background and relevant work

2.1. Visual variables in cartography

Bertin (1983) first described a system of visual variables to encode attribute information in cartography using symbolization (White, 2017). Visual variables serve as a graphic vocabulary for expressing geographic information on maps and other graphic representations. The original system from Bertin comprises location, size, shape, hue, color, texture, and orientation. Appropriate symbolizations are based on the empirical level of measurement of the visualized data, whether nominal, ordinal, interval, or ratio, with certain visual variables being better suited to symbolize certain measurement levels. Visual variables can be used flexibly and in conjunction with one another, and are sometimes double-encoded. For instance, two visual variables may be used to express the same attribute information, potentially creating a stronger graphical effect in combination (Roth, 2017).

Bertin's original system has since been expanded by others (Roth, 2017; White, 2017). DiBiase et al. (1992) identified three principal variables for animated (dynamic) maps: duration, order, and rate of change. MacEachren (1995) extended this list to include display date, frequency, and synchronization. These new visual variables are justified by advancements of technologies in Geographic Information Science, which now allow for dynamic and temporally-varying displays. Specific to movement visualization, Graser et al. (2020) describes the use of visual variables in depicting aggregated movement, such as through point marker density and the use of color for mean speed of movement, with a grid-based approach. Although we focus on individual recorded trajectories rather than aggregates, the connection to recorded movement tracks is a relevant consideration. This additionally demonstrates the use of point-based visualizations to depict movement.

Although the original system of visual variables has been further developed to adopt it to new computer cartography methods (Roth, 2017), it is critical that components of the system be evaluated in the context of expanding data visualization needs. For instance, we must assess the potential value of using animation in map displays (Goldsberry & Battersby, 2009; Griffin et al., 2006), particularly for mapping movement phenomena and trajectories. Many current design choices in cartography continue to be based primarily on aesthetics and convention, with less emphasis on visualization design principles supported by empirically and systematically user-tested studies. Therefore, there is a need to build a cohesive research program for evaluating these design conventions and newly-enabled approaches to visualization. This in turn will further support new insights in visualization-based communication and decision-making (Padilla et al., 2018).

2.2. The cognitive evaluation of geovisualizations

In a human-centered approach to knowledge discovery from movement data (Dodge & Noi, 2021), cognitive evaluations are essential for supporting the human users' interpretation of extracted patterns. Cognitive evaluation in geographic visualization work presents a key opportunity to learn how to support efficient visual communication of complex spatiotemporal information – such as in movement visualization – for research purposes and applied decision-making. It is necessary that we have the tools for testing claims about the effectiveness or plausibility of a visualization. Displaying information in ways that take advantage of our shared cognitive facilities, integrating insights from psychology, can allow cartographic design to follow principles for a more natural and efficient understanding of large multidimensional data (Ware, 2013c). For instance, one of the central methods of supporting visual perception in the visualization of quantitative data is to piggyback on our use of spatial metaphors in cognition. This takes advantage of human cognition of existing metaphors, such as our understanding of the "more is more" visual metaphor commonly exploited in the visual display of quantitative information (Tufte, 2001). For example, this can be used to express higher values with taller bars in a graph or darker colors in map symbology. The clear, cognitively based communication of information through visual means can help both novices and experienced practitioners grasp concepts more readily.

With the widespread increase in the availability and the demand for processing space-time activity data (Miller, 2005), people increasingly use information displays with high visual and cognitive load. However, it is not always clear what level of complexity and realism is appropriate for geographic visualization displays (Hegarty et al., 2012). It is therefore essential to evaluate the communicative efficiency and effectiveness of various aspects of complex visual displays in helping people understand information conveyed along both spatial and temporal dimensions. There is increasing support for undertaking cognitive research into the design and interpretation of cartographic visualization approaches (Fabrikant et al., 2010). This approach highlights the importance of understanding how internal cognitive processes interact with external visualization tools (such as maps). Relevant work includes the empirical evaluation of spatiotemporal data visualization through animated maps (Griffin et al., 2006; Harrower, 2007) and the adaptation of map displays based on context (Griffin et al., 2017).

Other related work looks at a specific class of geovisualizations, the flow map, to identify and justify best practices for communicating flow information between locations (Gu et al., 2018; Jenny et al., 2018). For instance, Dong et al. (2018) assess the usability of flow maps using eye-tracking and evaluation tasks to compare straight-line versus curved-line flow visualizations, as well as color versus thickness of lines. We mainly focus on discrete trajectories here, representing the paths of individuals over time. With trajectories, movement parameters and their variations can be visualized along the path as the individual moves over time. In contrast, flow lines and flow matrices are used to represent speed and other movement parameters at the aggregate and summary level at different locations or during the entire flow line. Also, relevant to the comparison of spatiotemporal information through point-based visualizations and additional visual variables is the example by Fukaya and Misue (2018). Although dealing with shipping vessels, the example visualizations (such as varying the hue, saturation, and size/radii of dots) for the vessels' movement trajectories in the paper are similar in terms of data recording and potential visualization styles for animal movement trajectories.

There is no better example of expressing the importance of time in visualization as movement data (Dodge, 2021; Kraak, 2014). Movement is necessarily spatiotemporal: it refers to the change in spatial location over time – but limited empirical evaluation has been conducted on how people perceive time in geographic displays of movement behavior between static and dynamic displays. Some have looked at the impacts of using animation more generally in cartography, for instance in the animation of choropleth map displays (Fish et al., 2011; Goldsberry & Battersby, 2009). Such work suggests, however, many remaining gaps in our understanding: for instance, which aspects of static display form design and symbolization translate to communicating dynamic change (see the example of choropleth maps by Battersby & Goldsberry, 2010). This work fundamentally contributes new insights into human cognition of spatiotemporal visualizations and provides novel methodological approaches to the evaluation of visual representations of movement.

2.3. The cartographic framework for movement visualization

Figure 1 presents a cartographic framework for movement visualization, adopted from the pyramid model of movement representation (Dodge & Noi, 2021; based on the triad model proposed in Kraak, 2014). In this study, we evaluate the efficacy of various elements of this framework to help the human user in understanding of movement data. The core elements of the framework are as follows. The text highlighted in dark gray in Figure 1 represents the aspects included in the present study.

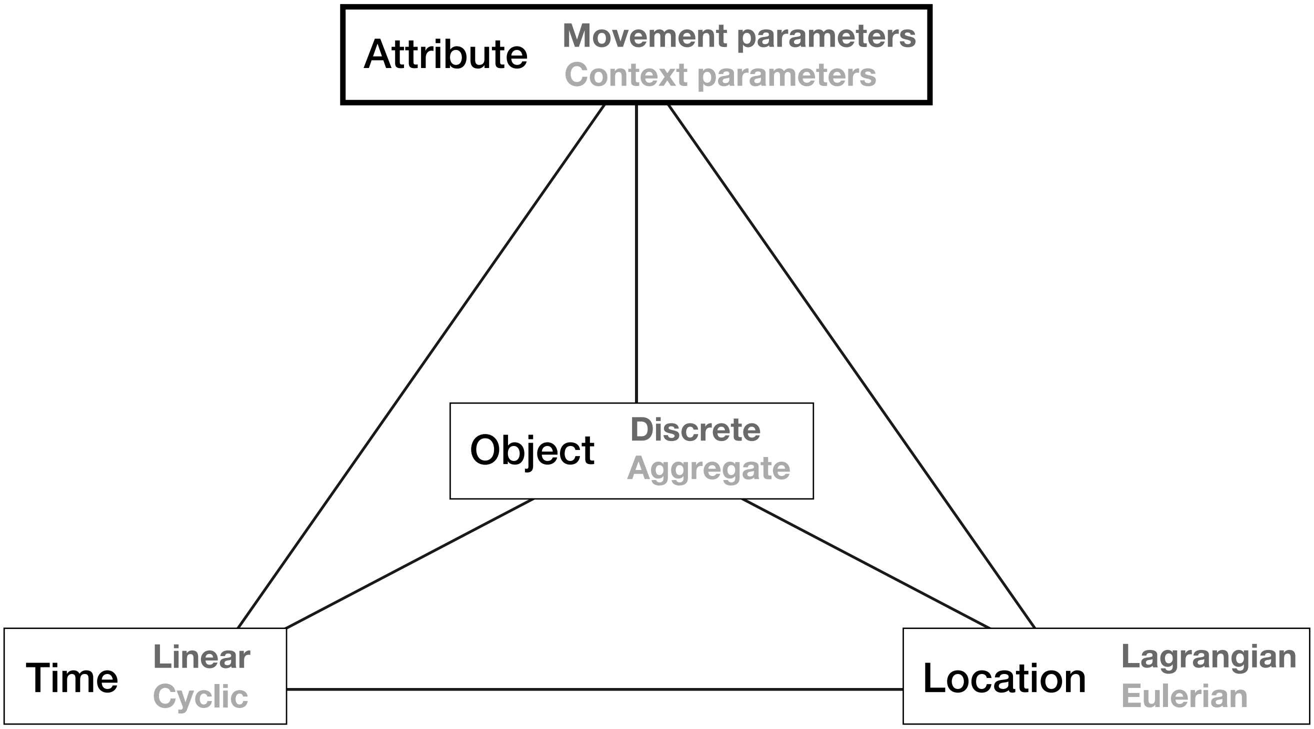


Figure 1. The cartographic framework for mapping movement, adapted pyramid model of movement representation (Dodge & Noi, 2021).

- **Object**: Object refers to the moving phenomena represented in the visualization, either in terms of discrete trajectories of moving entities or aggregate indices such as Origin-Destination (OD) flows or other types of mobility indicators (see, for example, Noi et al. (2022)). This study focuses on "trajectories" as time-ordered sets of locations representing the movement paths of one or more moving entities as discrete objects.
- **Attribute**: Attributes refer to parameters characterizing movement and its internal and external contexts, such as movement parameters (e.g. speed, direction), behavioral state, environmental condition, etc. Attributes can be derived from movement trajectories or can be measured and recorded using auxiliary sensors through multimodal tracking, or they can be obtained from additional data sets such as remote sensing data. Attributes can be represented as numerical, ordinal, and categorical values and annotated to the trajectories. This study focuses on the evaluation of visual representation of movement parameters such as speed and direction using various forms of visual variables.
- **Time**: Time includes temporal information about movement, including start, end, duration, and frequency of movement events. Time can be expressed in different ways in visualization, such as through text, graphs, timelines, animation speed, etc. (Frank, 1998). It can be represented in a linear or cyclic fashion. We use a linear representation of time in this study.
- **Location**: Movement can be observed in space and time through two different perspectives: Lagrangian and Eulerian (Dodge, 2021). We focus on the Lagrangian perspective of movement, where individuals' movement locations are observed from the perspective of the moving entity along its path over time; in the Eulerian perspective, movement is observed at certain fixed locations.

Movement trajectories can be mapped using two-dimensional maps and three-dimensional space-time cube representations using static and dynamic displays. Dodge and Noi (2021) describe a taxonomy of techniques and tools available in the literature for mapping movement and flows. Taking the framework in Figure 1, this study evaluates two-dimensional depictions of discrete movement using static and dynamic displays. We use a Lagrangian mode of movement observations, with time treated as linear, to assess user interpretation of movement parameters, including distance traveled along track, displacement from starting point, turn angle, and spatial range. This work allows us to determine the advantages and caveats associated with different display forms for the visual representation of movement data and how they relate to cartographic visual variables. Elements shown in the framework in light gray serve as potential aspects of mapping movement to be evaluated in future studies.

3. Methods

In this study, we compare the use of static (fixed) versus dynamic (animated) display forms and visualization designs based on visual variables for representation of movement and its attributes. The central **hypothesis** is that the cognition of spatiotemporal movement visualizations is impacted by display choices, contingent on dynamism, with dynamic displays better supporting the effective understanding of movement parameters. We expect that movement parameters visualized through static displays are simpler (and therefore faster) to interpret, because these displays run less risk of information overload, but they may also fail to completely and precisely describe movement. To investigate this hypothesis, the study is guided by two **objectives**: (1) Determine how well static or dynamic display forms support peoples' ability to identify and understand movement through complex visualizations. (2) Compare the visual variables of shape, size, and color to establish which visual variables have greater affordances for displaying movement parameters (speed, acceleration, distance, and direction) in absolute and relative terms using spatiotemporal visualizations.

3.1. Research design

The study was administered online through a Qualtrics web-based survey platform. This study employed a between-subjects design, in which participants were assigned randomly to either a static or dynamic display condition. See Figure 2 for a diagram of the study flow. Depending on the assigned condition, all movement visualizations used in the study tasks were displayed either as a static image or a dynamic animation (video clip), each with a similar visual appearance and without map interaction elements such as zoom or pan capabilities except for selection by click. Whether assigned to the static or dynamic study condition, each participant had the same initial forms to complete related to consent to participate, demographics (age, gender, education level, field of work, and location), and the individual difference measures of sense of direction and GPS reliance (described in detail in Section 3.4 below).

Participants used geographic visualizations of movement trajectories of animals (described in Section 3.2) to complete the study tasks (described in Section 3.5). The tasks aimed at assessment of visualization of movement parameters in absolute or relative terms. Identification tasks focused on assessing movement parameters including pausing, changes in speed, changes in direction, and direction of movement. Comparison tasks asked participants to determine the relationship of speed between trajectory segments within a single trajectory and between separate movement tracks. The

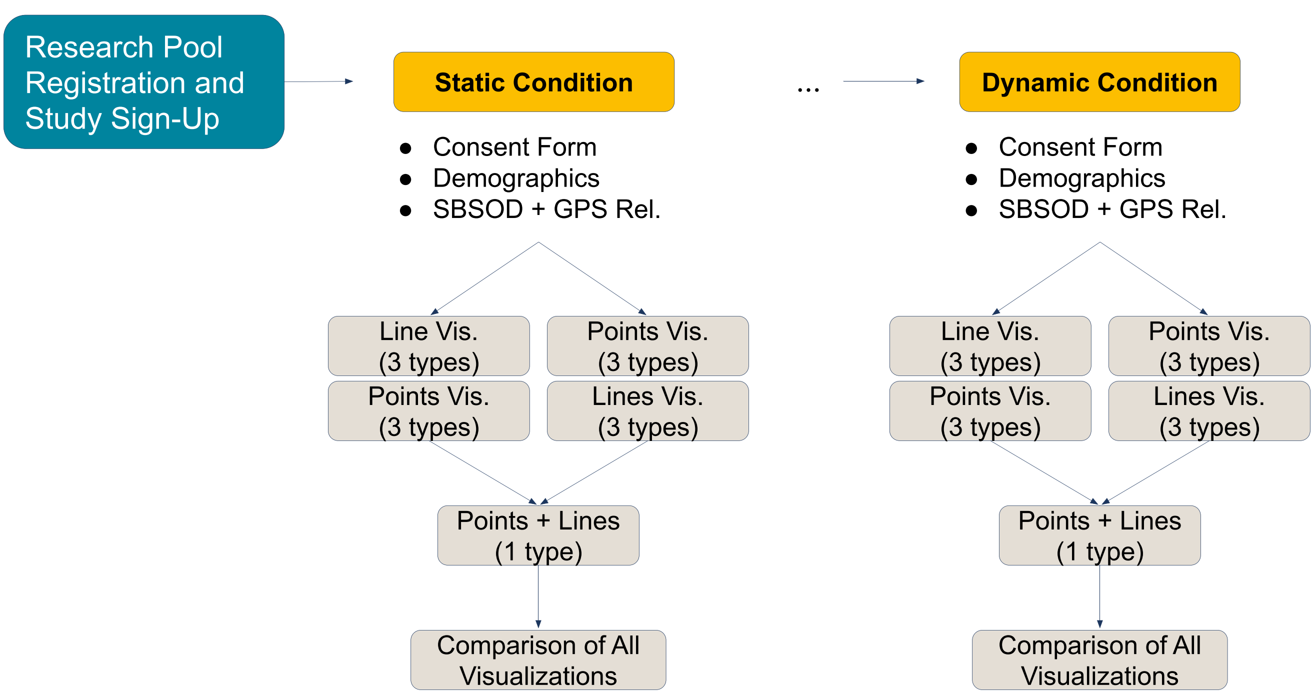


Figure 2. Study design and the workflow of the experiments.

same set of task questions were repeated for each of the seven visualization designs; all participants completed all tasks for all seven designs. As shown in Figure 2, the order in which the visualization designs were presented to participants was counter-balanced by showing half of the participants in each condition the line-based visualization designs first, and showing the other half the point-based visualizations first. This allows us to compare the types of designs while accounting for order effects, such as possible preference for the first designs viewed.

3.2. Visualization designs

In exploratory movement data analysis using discrete trajectories (Dodge & Noi, 2021), it is important that visualization techniques can effectively convey important information about movement parameters and their variations along the individuals' path or across different paths. Therefore, identification and comparison of speed, direction, and recognition of relative motion patterns (Laube et al., 2005) are important tasks in exploratory movement analysis for both movement ecology and human movement applications. In this study, we include tasks to assess the efficacy of various visual variables in conveying information about movement speed, acceleration/deceleration, direction, and relative movement using both static and dynamic displays.

To complete the tasks, participants used the seven different visualization designs as shown in Figure 3. To create the visualizations, we generated 2D displays of movement trajectories using points and lines in DynamoVis (Dodge et al., 2021). The design of each visualization was systematically varied along the visual variables of shape (lines versus points), color, and size (line width or point size), representing movement parameters of speed and acceleration (Bertin, 1983; White, 2017). Each visualization displays a unique one-day movement track of an animal recorded using GPS at a 1-h interval (in this case a tiger; see Ahearn et al. (2017) for more details on the data set). We used one-day tracks for each to create comparable length trajectories for the visualization designs.

Of the seven visualization designs (Figure 3), visualization designs 1–3 were line-based, visualization designs 4–6 were point-based, and visualization design 7 used a point-based visualization combined with a subtle white line, connecting the sequence of points. This allowed us to create different visualization designs in which the speed of trajectories was encoded in the visualization designs using either color of the lines/points, size of the lines/points, or both. See Appendix B for an example of the visualizations as they appeared to participants in either the static or dynamic conditions.

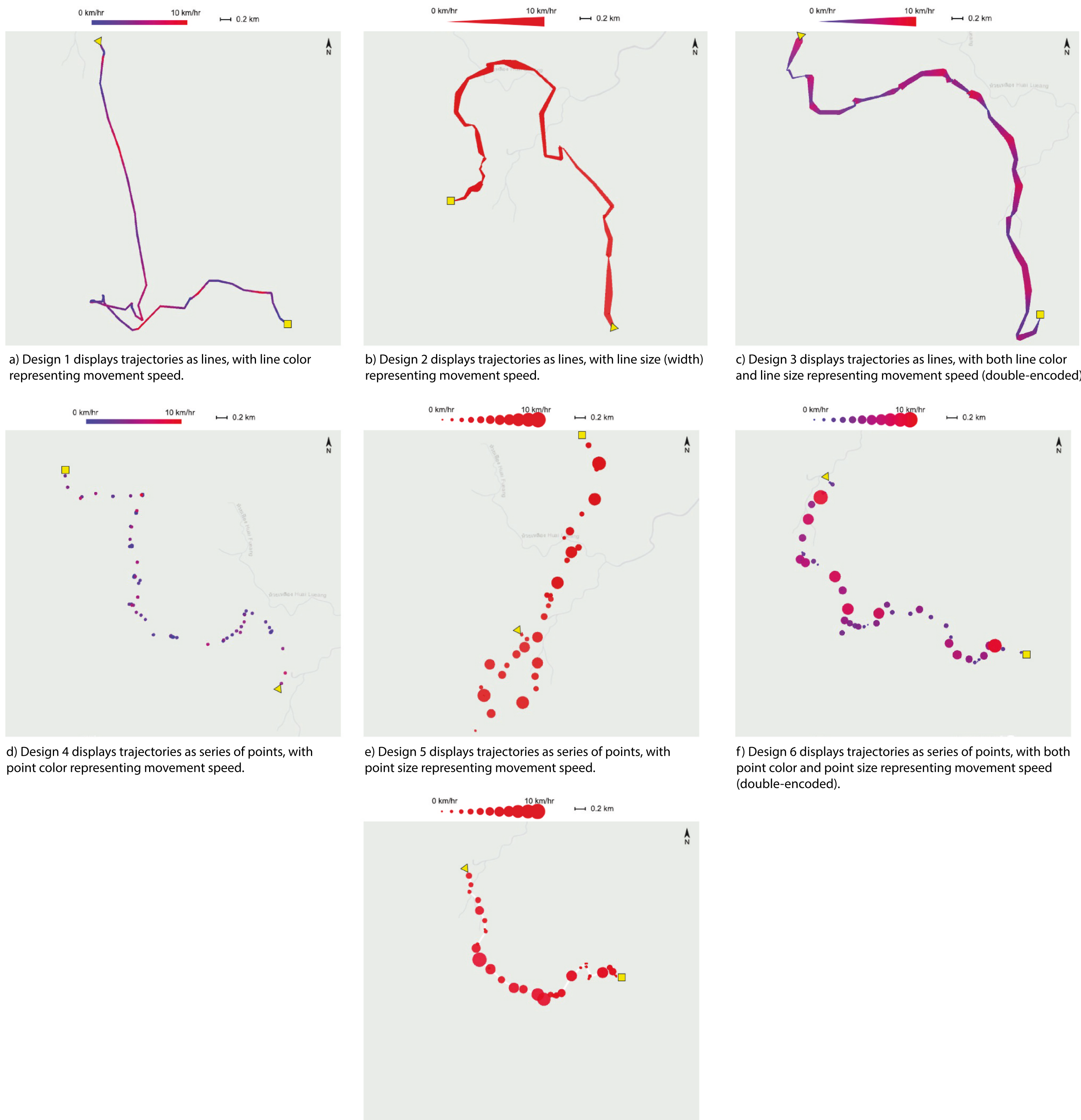
3.3. Participants and recruitment

We recruited 100 adult participants from a university pool of undergraduate students and our external distribution through e-mail lists. Power analysis reveals that a sample size of 45 participants in each condition would provide the statistical power to detect a medium effect size of .6 with a significance level of .05 at the .80 level (Cohen, 1992). Participants were recruited from the internal distribution ($n = 82$) through an online university research pool system (UGIG, https://ugig.app) serving the Department of Geography at the University of California Santa Barbara (UCSB), as well as through an external e-mail distribution to students at eight universities: UCSB, Georgia Tech, University of Minnesota, University of North Carolina Charlotte, University of Western Ontario (Canada), Swiss Federal Institute of Technology Zurich (ETH-Zurich; Switzerland), University of Applied Sciences Northwestern Switzerland FHNW, and RMIT University (Australia). The external distribution had a lower completion rate, resulting in a smaller number of useable participant responses ($n = 18$). Because internal and external participants were evenly distributed across study conditions, we combined participants from both distributions for the purpose of our general analysis. This work was approved by the University of California Santa Barbara (UCSB) Institutional Review Board under Protocol #1-19-0370.

Approximately half of all participants completed the static version of the study ($n = 53$) and the other half completed the dynamic version ($n = 47$). The number of participants in each of the two main conditions was not equal due to differences in completion rates, with slightly more attrition for participants assigned to the dynamic condition. Descriptions of initial data cleanup and removal of incomplete responses ($n = 34$) are provided in Appendix A.

3.3.1. Demographics

Of our 100 participants, the gender breakdown is 64 female and 36 male participants. The skew toward female participants is representative of the departmental research pool and the typical completion rate of study participation. The age of participants ranges from 18 to 46, with a mean of 21.3 years old. This younger age range is not surprising, given that many of the participants are drawn from an undergraduate student



a) Design 1 displays trajectories as lines, with line color representing movement speed.

b) Design 2 displays trajectories as lines, with line size (width) representing movement speed.

c) Design 3 displays trajectories as lines, with both line color and line size representing movement speed (double-encoded).

d) Design 4 displays trajectories as series of points, with point color representing movement speed.

e) Design 5 displays trajectories as series of points, with point size representing movement speed.

f) Design 6 displays trajectories as series of points, with both point color and point size representing movement speed (double-encoded).

g) Design 7 displays trajectories as both points (with point size representing movement speed) and lines (underlying line representing movement path).

Figure 3. All 7 visualization designs. The animal's movement track is shown with a line or series of points, the yellow arrow indicates the beginning of the track, and the yellow square indicates the end of the track. The GPS track is recorded at the temporal interval of 1 hour.

population, with 71 of our 100 participants reporting high school or GED degree as their highest level of education completed. The most represented field of study or work was Psychology (selected by 5% of respondents), followed by Geography or GIS (1.5%), Other (1.5%), and the Social Sciences generally (1.3%), which means participant backgrounds are quite broad.

Because the study was conducted remotely, the location of participants varied widely. The majority of participants were located in the United States, and most of them were located in California at the time of completion. Other countries represented in the participant pool were China, Australia, Switzerland, and Canada. Due to data collection occurring during the COVID-19 pandemic, even participants from the home university were not necessarily located near campus at the time of study completion. One participant reported a known color vision deficiency (specifically, red-green colorblindness). We do not exclude the participant response in our analysis because our red-blue color palette was likely to still be distinguishable in those visualizations which used color to encode speed.

3.4. Individual difference measures

We assess participants on two measures of individual differences: sense of direction and GPS reliance. These measures and survey instruments are described as follows:

(a) *Sense of direction* is measured with the Santa Barbara Sense of Direction (SBSOD) scale (Hegarty et al., 2002). The SBSOD is a self-reported measure which asks participants to rate their level of agreement with 15 statements on a 7-point Likert scale. The resulting score has a possible range of 1.0 to 7.0 (the higher value being the better sense of direction); for our participant pool, responses ranged from 1.3 to 6.8 with an average SBSOD score of 4.3 across all participants.

(b) *GPS reliance* is measured using the GPS reliance scale of the McGill GPS questionnaire (Dahmani & Bohbot, 2020). This scale asks participants to rate their agreement with 7 statements on a 5-point Likert scale. Our participant responses range from 15.0 to 33.0 with a mean of 24.3.

Sense of direction does not appear to differ between study conditions (static vs. dynamic), $t(98) = -0.81$, $p = 0.42$. However, sense of direction does significantly differ by gender, $t(98) = 4.6$, $p < .001$. Male participants in our study have a higher average SBSOD score ($M = 4.95$, $SD = 1.22$) than female participants ($M = 3.9$, $SD = 1.02$), and the direction of this relationship is consistent with the existing literature for SBSOD by gender (Hegarty et al., 2006). It is unclear how much self-reported sense of direction contributes to map interpretation; correlational studies that look at gender differences in map reading or map interpretation show mixed results, with no necessary male advantage (Coluccia & Louse, 2004).

Similarly to sense of direction, GPS reliance does not appear to differ between study conditions (static vs. dynamic), $t(98) = 0.55$, $p = 0.58$, but does significantly differ by gender, $t(98) = -3.55$, $p < .001$. Female participants in the study have a higher average GPS reliance score ($M = 25.5$, $SD = 4.43$) than male participants ($M = 22.22$, $SD = 4.45$), meaning they report more reliance on GPS in their daily and occasional travel.

These patterns for the sense of direction and GPS reliance suggest that there is no significant difference between participant conditions, meaning those assigned to the static and the dynamic conditions are similar on these measures of individual difference. For comparisons between these individual difference measures, results show that there appears to be a significant and fairly strong negative relationship between sense of direction and GPS reliance ($r = -0.39$, $p < .001$), meaning those with better sense of direction show less GPS reliance. This may indicate that those with a better sense of direction are less reliant on GPS for navigation, or that those who refer to GPS devices less often to navigate have a better sense of direction. In Section 4.3, we compare these individual difference measures with participant success measures in the study.

3.5. Study tasks

The study tasks include assessment tasks related to absolute (i.e. value at a certain location) and relative (i.e. change over a time period or difference in values across tracks) speed and direction, comparisons of movement tracks, description of movement tracks, and visualization ratings based on participant perceptions of ease and efficacy. Tasks are selected for the study based on the primary movement analysis tasks necessary to enable more complex movement behavior interpretation tasks (Nathan et al., 2008). Our focus is on assessing how users evaluate speed and direction, as they are central to the basic evaluation of movement patterns (Dodge et al., 2008), and are therefore critical tasks to the identification of behavior by movement ecologists.

3.5.1. Assessment of absolute and relative speed and direction

In our study, identification task questions relate to absolute and relative movement speed and direction. Context is provided with a text description stating, "In this series of tasks, you will be assessing the speed and direction of an animal's movement. The key (legend) at the top of the map explains how you can understand the information represented." Actions to identify include: *Stop Movement (Pause)*; *Change Speed from Low to High (Speed Up)*; *Change Speed from High to Low (Slow*

Down); and *Major Change in Direction*. For each of these questions, 1 "time" refers to one instance of that action, such as one stop (zero speed value) or one change in direction over the duration of the trajectory. See Figure 4 to see the four questions asked in the identification task. We assess identification tasks based on the distribution of responses and the amount of variation between participants' responses, rather than given an objective accuracy score for these questions. This is because counts of movement actions may be subjective, based on varied interpretations of the parameters to identify actions such as "stopping" or "speeding up." This is further described in Appendix C.1.

3.5.2. Overall relative direction

In the direction identification questions, participants are asked to identify: "What is the overall direction of the animal's movement from the beginning to the end of the track?" A compass rose is presented to participants to select a response by clicking one of the directions labeled for eight cardinal directions (N, NE, E, SE, S, SW, W, NW). The compass rose is oriented with a typical north-up orientation, as is each of the visualizations presented in the study. Responses to these questions are given a score of 1 for each visualization with a correctly identified direction.

3.5.3. Absolute speed identification

For each visualization, participants are additionally asked to identify the fastest point (i.e. the location of the highest speed value) along the animal's track by selecting a point on the visualization image itself: "At which point does the animal appear to be moving the fastest in this track? Click to add a point on the image below." Responses are counted as correct if they correspond with a point on the movement track visualization where measured speed falls within the top 10% of overall movement speed. Fastest speed responses are scored (given a score of 1) if participants correctly identified a point on the movement track visualization where measured speed fell within the top 10% of overall movement speed. This assessment is described further in Appendix C.2.

Answer the following questions about the map shown above. How many times does the animal do the following along the track displayed on the map?

	0 times	1	2	3	4	5	6	7	8	9	10+ times
Stop Movement (Pause)	○	○	○	○	○	○	○	○	○	○	○
Change Speed from Low to High (Speed Up)	○	○	○	○	○	○	○	○	○	○	○
Change Speed from High to Low (Slow Down)	○	○	○	○	○	○	○	○	○	○	○
Major Change in Direction	○	○	○	○	○	○	○	○	○	○	○

Figure 4. Format of the response form presented to participants for the identification tasks.

3.5.4. Comparisons of movement tracks

These tasks include within-track and between-track comparisons for relative movement speed and distance. Within-track comparison questions ask participants to make a speed comparison between two selected segments of a single movement track. The question prompt reads, "Was the animal moving faster overall in Segment A or Segment B?" Participants are shown the map of movement previously displayed for the Identification Tasks, with additional call-outs of two segments highlighted by a box and labeled "Segment A" and "Segment B," with the rest of the track and background grayed out. See Figure 5 for an example of segments presented to participants for within-track comparison. Between-track comparison questions ask participants to make comparisons between two movement tracks, with each track representing the movement of a different animal during the same period of time. These between-track questions ask:

- Choose which track segment appears to indicate faster overall movement.
- Which animal covered a longer distance during the track?
- Which animal moved further away from the beginning point of their track?

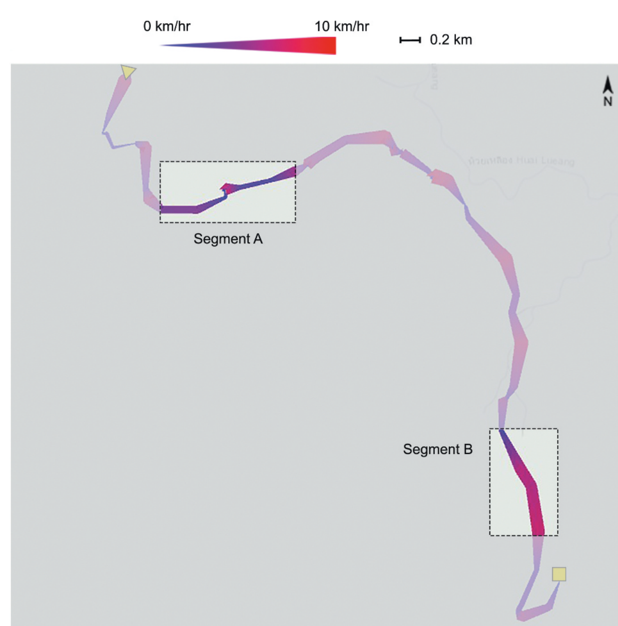


Figure 5. Visualization 3, presented with two highlighted segments for comparison.

- Which animal appears to have covered a larger area (spatial range)?

Participants were given a score of 1 for each accurate response, for each of the five questions described in this section, for each of the seven visualizations.

3.5.5. Description of movement tracks

Participants complete a set of open-ended description tasks for each visualization design using a brief text entry. For these tasks, participants again use the previously displayed map with call-outs of the two highlighted segments (e.g. Figure 5). Participants are asked to describe the movement of the tracked individual over each segment, specifically related to speed, acceleration, and direction of movement in each segment. The prompt reads: “Describe movement speed and direction in Segment A [or B]. No need to use complete sentences.” Two examples of the response format are provided in the instructions: “moving east at a constant speed” and “speeding up while moving NW.” To systematically characterize participant descriptions of movement, we take a text processing (term frequency) approach to identify commonalities between descriptions. Responses to these description questions are assessed by looking at frequency of descriptive phrases used to describe the movement within the selected segment for each of the seven visualizations. For a detailed description of the text processing approach, see Appendix C.6.

3.5.6. Visualization ratings

To assess participant perceptions of the ease and usefulness of the visualization designs, we ask a set of rating questions related to ease of understanding and perceived efficacy of visual elements. Participants rate each of the seven visualizations based on these three prompts:

- Ease of Understanding: “Rate your ease in using these visualizations for the identification and comparison tasks in the study.”
- Efficacy for Assessing Movement Speed: “Rate the efficacy of each visualization for conveying information about movement speed.”
- Efficacy for Assessing Movement Path: “Rate the efficacy of each visualization for conveying information about movement path and direction.”

For the ease of understanding prompt, responses are given using a 5-point Likert scale from 1 being “very difficult” to 5 being “very easy,” with a rating of 3 being neutral (“neither easy nor difficult”). For the second two prompts related to efficacy of visual elements, participants are asked to rate each of the 7 visualizations for conveying movement speed and for conveying movement path and direction based on a 5-point Likert scale from 1: “very unclear” to 5: “very clear.” These rating questions measure the participants’ perceptions of visualization design efficacy and therefore complement the other quantifiable study task measures. In this way, we provide measures both of participants’ accuracy of interpretation (as in the tasks above), as well as their perceptions related to the ease and usefulness of these visualizations for doing so.

4. Results

This section presents the results of the study with relation to the two research objectives presented at the beginning of Section 3. Briefly summarized, the objectives are to determine the relative effectiveness of (1) static and dynamic display visualization forms, and (2) the visual variables of shape, size, and color for communicating the movement parameters. This section summarizes the results in terms of response time for tasks, responses to identification questions, task success scores (accuracy), open-ended descriptions of movement, and participant ratings of the visualization designs based on perceived ease of use and perceived usefulness of each design. In this way, we look at several complementary metrics for evaluating the efficacy of these visualization designs for communicating movement information: timing, variation in interpretation, accuracy on tasks, and user perceptions of efficacy.

4.1. Response time

We measure duration for overall completion of the study, as well as comparing response time for all tasks, by study condition (static vs. dynamic), and by task type. For overall timing, the shortest completion time for the entire survey is 21 min and the longest completion time is 113 min (nearly 2 h). Median completion time for the task questions, excluding the time for demographics and individual difference measures, is 32.1 min ($SD = 12.5$ min). Median time taken for tasks in the static condition is 28.8 min and in the dynamic condition is 33.1 min, with no significant difference between conditions. For time spent on tasks, the Wilcoxon (Mann-Whitney) rank sum test with continuity correction reveals no significant difference between study conditions (static vs. dynamic), statistic = 1393, $p = 0.31$. Therefore, it takes participants a comparable amount of time in the static and the dynamic conditions to complete the visualization task questions. Overall response times for sets of questions by specific visualization design are recorded. However, since the response times for individual task questions are not recorded, we acknowledge that the specific interpretation task is likely to impact timing and should be further distinguished in future work.

As participants complete the same set of task questions for each visualization type, we also compare timing across each visualization design. For time spent on tasks by visualization type, the Kruskal–Wallis test shows significant differences between groups ($\chi^2 = 47.22$, $p < .001$, $df = 6$). To identify where there are significant differences between visualization designs, we run pairwise comparisons (see Appendix C.3 for reported differences) and find that Visualization 7 takes participants significantly less time to complete as compared to all other visualization designs. Visualization 7 is the combined visualization design, which uses a point-based representation and an underlying line connecting the sequence of points (see Figure 3). However, Visualization 7 tasks are presented as the final set of questions to all participants (while the order for the previous visualization blocks is counterbalanced), so order may relate to the faster completion time with Visualization 7. The difference between Visualizations 2 and 3 may also be due to order effects *within* the block. Furthermore, across both static and dynamic conditions, tasks take participants 4.81 min per line-based visualization (1, 2, 3) and 4.49 min per point-based visualization (4, 5, 6) on average, which is not significantly different across conditions. The Wilcoxon rank sum test reveals that task completion time for each visualization does not significantly differ between the visualization blocks, statistic = 63533, $p = 0.18$. We therefore assert that overall time differences between visualizations based on shape (line vs. point visualizations) are not meaningful. We also compare time differences between line-based and point-based visualization tasks within the static participant group and the dynamic participant group and find no significant differences.

4.2. Assessment and identification tasks

We first observe the distribution of responses in participants' identification of movement actions in the study. For identification tasks, distribution rather than accuracy is assessed; for accuracy or task success, see sub-section 4.3. In some cases, as summarized in Table 1, response distributions significantly differ based on condition, more often for identifying number of stops. For Visualizations 2, 3, and 5, participants in the dynamic condition report more stops than those in the static condition, potentially signaling that pauses in movement are more salient when the movement track is animated. Participants in the static condition report more accelerations (speeding up) for Visualization 4 than do those in the dynamic condition, and also more decelerations (slowing down) for Visualization 5. Participants do not differ by condition in their identification of major changes in direction for any of the visualizations, so we are not able to say that participants identify more or fewer directional changes based on whether they use the static or dynamic display forms for this task.

Table 1. Comparison of response distributions to identification tasks in static vs. dynamic conditions. Only significant differences in distributions reported. DYN = Dynamic; STA = Static.

	Vis 1	Vis 2	Vis 3	Vis 4	Vis 5	Vis 6	Vis 7
Stop movement		DYN	DYN		DYN		
Speed up				STA			
Slow down					STA		
Major change in direction							

4.3. Overview of task success scores (accuracy)

Total task success scores are a summary measure of all questions which were scored based on accuracy. These include the tasks related to Overall Direction, Fastest Speed Identification, and Comparisons of Movement Tracks. Combined scores across all the tasks and visualization designs range from 24 to 41 ($M = 34.05$, $SD = 3.1$), with a maximum possible score of 49 across all tasks, comprising 7 questions marked as correct or incorrect for each of 7 visualization designs.

Observing individual differences in relation to total scores of participants across all tasks for each visualization design, we find no reliable relationships between individual difference measures and total scores. In other words, there is no significant relationship between total score and sense of direction ($t(98) = -0.72$, $p = .47$), nor between total score and GPS reliance ($t(98) = -0.35$, $p = .73$), nor any difference in total scores by gender ($t(68.23) = -1.40$, $p = .17$).

4.4. Overall success by static versus dynamic display forms

With regard to research objective (1), we first evaluate success across the two participant conditions to compare the use of static versus dynamic display forms. Figure 6 shows total scores across the study conditions. The static and dynamic visualization display forms do not appear to impact success at the aggregate level, based on the set of movement identification and comparison tasks presented in the study. There are no significant differences in overall success scores across the

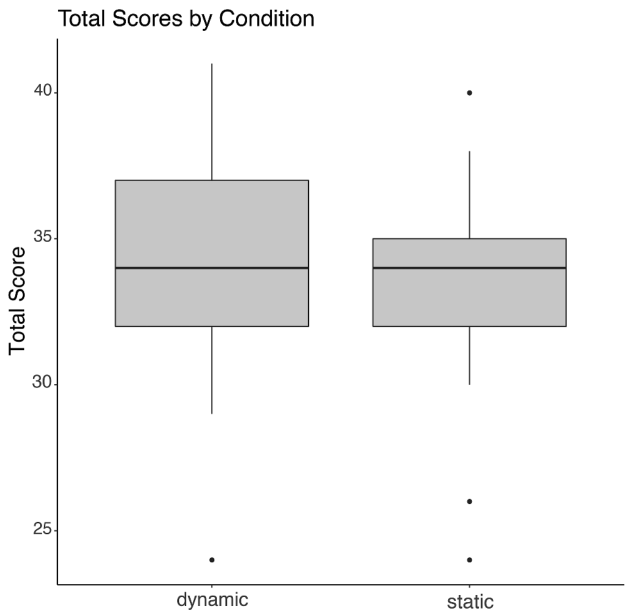


Figure 6. Total scores for all tasks and visualization designs, comparing participants in static vs. dynamic conditions.

above tasks between participants randomly assigned to use the static versus the dynamic display forms. Participants in the static condition have a similar total score ($M = 33.66$, $SD = 2.7$) to those in the dynamic condition ($M = 34.49$, $SD = 3.5$), of a maximum possible score of 49, with no significant difference between the groups, $t(86.72) = 1.3$, $p = .19$.

4.5. Overall success by visual variables

To evaluate the research objective (2), which is to compare the use of different visual variable encoding of movement parameters, we compare participant success on tasks by visualization type. Broadly, we categorize the seven visualization designs across the two display form conditions into four visualization blocks, which we identify as *static lines*, *static points*, *dynamic lines*, and *dynamic points*. In doing so, we note differences in task scores based on encoding through the visual variables, as assessed through the visualization designs.

The results comparing scores on tasks for the line-based versus point-based visualizations suggest that participant success differs significantly based on visualization design. For participants across both static and dynamic conditions, task scores are higher on average on the sets of tasks using line-based visualizations ($M = 5.32$, $SD = 1.21$) than they are on the sets of tasks using point-based visualizations ($M = 4.52$, $SD = 1.16$). Differences in success are more pronounced for those participants in the condition using dynamic display forms. The main effect of visualization block (static line-based, static point-based, dynamic line-based, dynamic point-based) is significant, $F(3, 696) = 35.27$, $p < .001$.

Figure 7 shows differences between overall task scores based on grouping by line-based and point-based visualization types. Whereas scores on line-based and point-based visualization tasks do not differ for static participants, scores are significantly higher for line-based tasks in the dynamic condition. The outcomes suggest that the connector trajectory line is an important visual cue when representing GPS tracking data, while animating trajectories can better capture changes in movement parameters. This also suggests that there may be an interaction between condition and design.

To further distinguish between *condition* (dynamic, static) and *design* (point-based, line-based), we construct a linear model with two factors, condition and design. To meet ANOVA model assumptions, we apply a Box-Cox power transformation to stabilize the variances in our dataset. The two-way ANOVA shows that the main effects of condition (dynamic vs. static), $F(1, 196) = 13.101$, $p < .001$, and design (point-based vs. line-based), $F(1, 196) = 128.225$, $p < .001$, are statistically significant. The interaction effect is also significant, $F(1, 196) = 21.617$, $p < .001$. This supports the finding that the scoring on line-based vs. point-based tasks is moderated by condition; however, the differences in means are relatively small. Detailed results are given in Appendix C.4. Future work should further investigate the types of visualization interpretation tasks that are supported by each type of visualization design (comparisons for individual task types in this study are described briefly in Appendix C.5).

4.6. Description of movement tracks

We next assess participants' responses to the open-ended movement track description questions, as

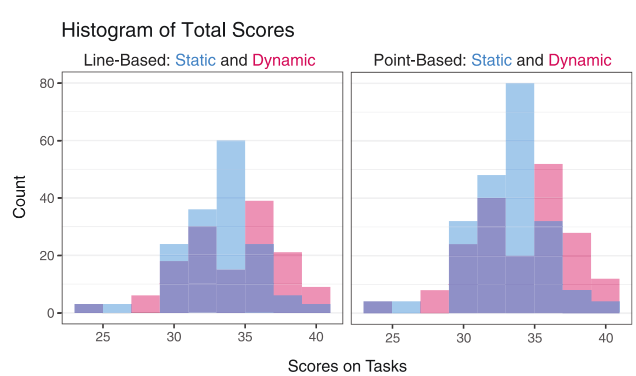


Figure 7. Task scores grouped by visualization type, comparing across static vs. dynamic conditions. Static histogram bars are shown in blue, dynamic bars are shown in red, and overlapping bars are shown in purple.

Table 2. An example of six participant responses to Visualization 3 segment description questions.

Visualization 3, Segment A
"moving somewhat slow in the NE direction" "moving NE at a constant speed" "moving slightly north east with slow speed before stopping picking up pace a bit then returning to the slow pace" "moving east at a constant speed" "Slight decrease in speed going roughly in the northeast direction."
Visualization 3, Segment B
"speeding up while moving in the S direction" "speeding up while moving S" "moving slightly south east while gaining speed" "speeding up while moving south" "Speeding up tremendously in the southward direction."

described in Section 3.5.5. Table 2 presents examples of the raw descriptions provided by participants for Segments A and B in Visualization 3, as shown in Figure 5. Even observing a small subset of descriptions shows the level of agreement between participants about the movement occurring in each of these segments. However, this subset also demonstrates variation in the level of detail given for change in speed and in describing direction (i.e. based on four cardinal directions or eight).

For a high-level summary of frequent bigrams grouped across visualization design types, we present wordclouds in Figure 8. A full description of the text processing approach is given in Appendix C.6. Wordclouds are generated from participant descriptions, which displays frequency of the bigrams through text size. Bigram frequency is analyzed and wordclouds are generated using the "quanteda" R package (Benoit et al., 2018). Overall, the text processing shows more description of *direction* for line-based visualizations and more description of *speed* for point-based visualizations, suggesting that those parameters may be more salient to viewers using those types of movement visualization designs.

4.7. Participant ratings of visualization designs

Participant ratings of each of the seven visualization designs are summarized in response to the three questions described in Section 3.5.6 above.

4.7.1. Participant ratings of ease of understanding

Figure 9 displays summaries of Likert score ratings for ease of understanding for each of the seven visualizations. One caveat for the participant rating questions and the open feedback questions is that there were missing responses for 7 participants in the dynamic condition due to a page in the study that was hidden on Qualtrics for a short period during data collection. Hence, the Likert responses for these questions are summarized for 93 participants rather than the full set of 100.

Across all participants in either condition, visualization design 2 has the highest overall positive ease of understanding ratings (59% positive) and visualization 4 the lowest (16% positive). All three of the line-based visualizations (Visualizations 1, 2, 3) are rated more positively than negatively for overall ease of understanding, whereas all three of the point-based visualizations (Visualizations 4, 5, 6) along with the point-and-line-based visualization are rated more negatively. Moreover, these outcomes suggest that the track complexity (having turns and loops, e.g. as in Visualization 5) seems not to impact the ease of understanding, and the proper use of the visual variables shape, size, and color can help to represent movement more intuitively.

4.7.2. Participant ratings of efficacy of visual elements

Figure 10 shows that the line-based visualizations (Visualizations 1, 2, 3) are most positively rated for supporting the interpretation of movement speed. Visualization 3, which encodes speed as both color and width of the movement path represented as a line, is rated most favorably with 73% positive responses. Visualization 4 is ranked most negatively with only 28% positive ratings. This may suggest that the visual variable size may be more helpful in communicating movement speed. While color and size can be effective variables to communicate movement speed in line-based visualization, the complexity of the track may impact the efficacy of these variables, especially when the connector trajectory lines are not present in point-based visualizations. In this case, it is possible that the poor ratings for Visualization 4 may relate partially to track complexity (and not only visualization inefficacy).

Figure 11 shows that Visualization 1 is ranked highest for supporting the assessment of the movement path and direction, followed by the other line-based visualizations (2 and 3) which are also ranked highly positively (over 80% positive ratings). Visualization 5 is ranked lowest, with more negative ratings (61%) than positive (22%). As with efficacy for assessing movement speed, the same general pattern holds for assessing movement path, where line-based visualizations are rated more positively and point-based movement visualizations are ranked more negatively. This indicates that participants felt that line-based visualization designs gave a better sense of where the animal went. However, we again see here that Visualization 5, which uses a more complex overlapping track, ranks low for rated efficacy in communicating direction.

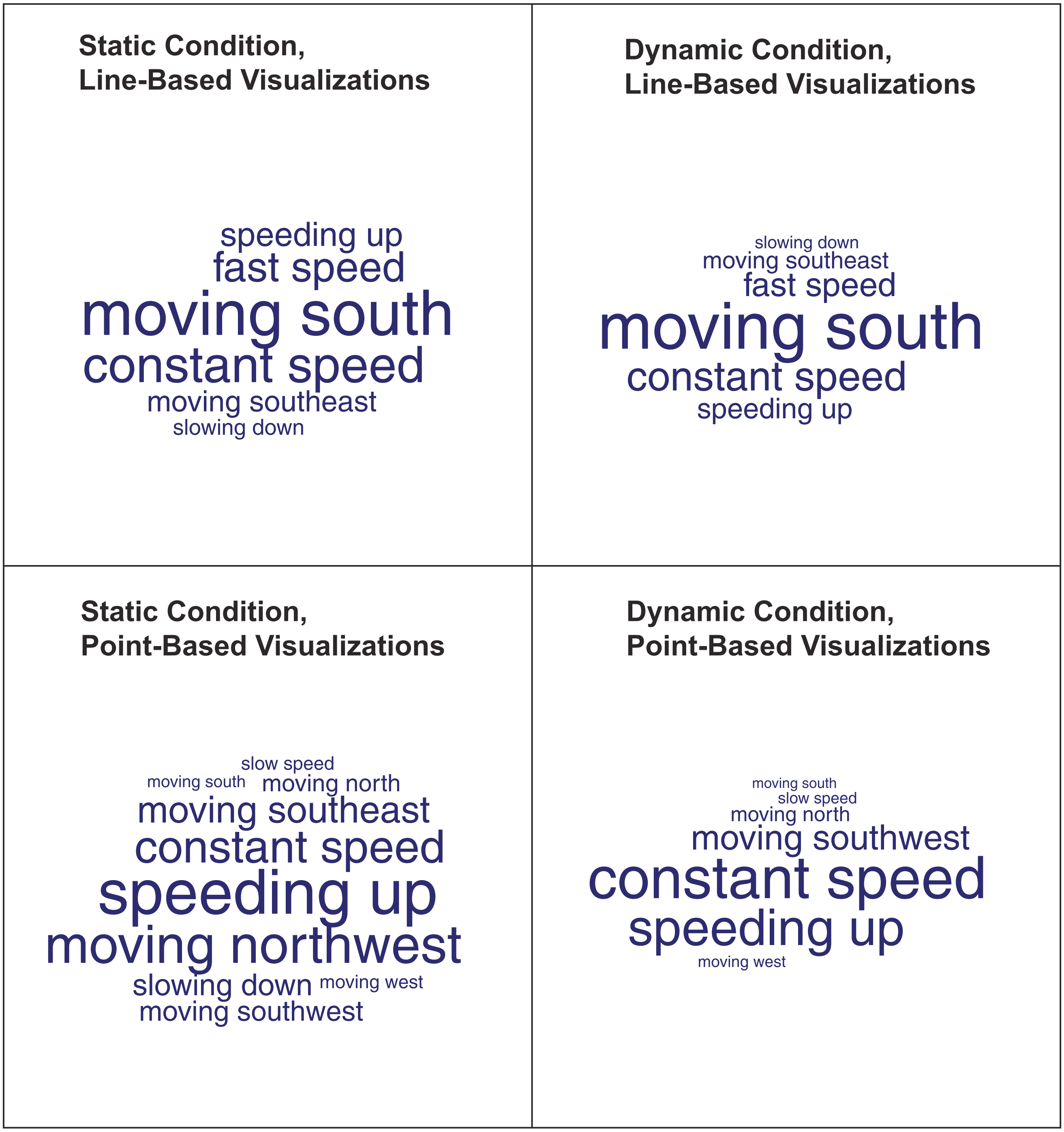


Figure 8. Wordclouds displaying frequency of bigrams in descriptions of static and dynamic line-based and point-based visualizations.

5. Discussion

5.1. Assessment of the results

Both static and dynamic display forms take participants a similar amount of time to interpret in the context of the study tasks. We also find no significant difference between participants in task completion time between blocks of visualization types (line-based vs. point-based). Therefore, we cannot say that static or dynamic displays, nor line- or point-based visualizations, are more efficient to use for the overall visualization of movement, especially when visualizing only one track as is the case for most tasks in this study.

With dynamic visualization styles becoming more commonplace, it is useful to know that the use of animated visualizations did not have a noticeable effect on time for interpretation. This is generally in line with

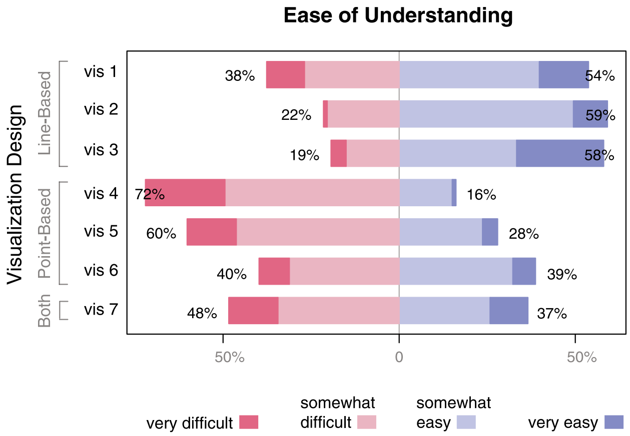


Figure 9. Likert plot of participant responses ($n = 93$) to ease of understanding questions. Percentages are given for negative vs. positive responses. Visualization designs 1 and 4 use the visual variable color, designs 2 and 5 use size, and designs 3 and 6 use both color and size. Design 7 uses size only.

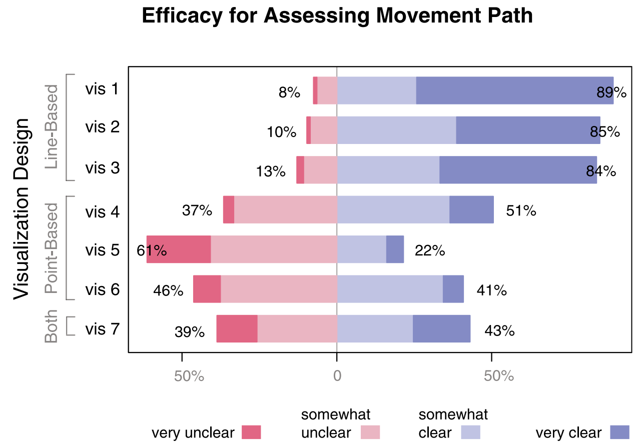


Figure 11. Likert plot of participant responses ($n = 93$) to efficacy of visual elements questions for movement path and direction. Percentages are given for negative vs. positive responses. Visualization designs 1 and 4 use the visual variable color, designs 2 and 5 use size, and designs 3 and 6 use both color and size. Design 7 uses size only.

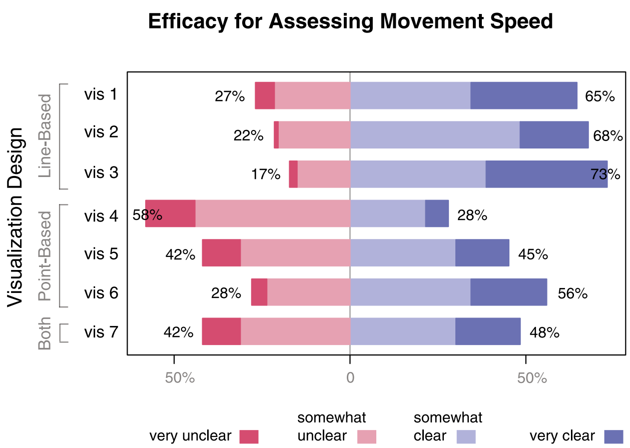


Figure 10. Likert plot of participant responses ($n = 93$) to efficacy of visual elements questions for movement speed. Percentages are given for negative vs. positive responses. Visualization designs 1 and 4 use the visual variable color, designs 2 and 5 use size, and designs 3 and 6 use both color and size. Design 7 uses size only.

previous work in static versus animated presentations of data visualizations, which has found little evidence for a reliable advantage of animations (Ware, 2013b). Some scholars have proposed that the cognitive effort involved with interpreting a static display may support information retention and the construction of internal cognitive models of the information (Mayer et al., 2005), but we do not explore longer-term effects or learning in this study, only task-related interpretation of information displays.

We find no significant difference in overall success (accuracy) scores between participants who used static versus dynamic visualizations. However, in terms of accuracy on tasks, trends in our results point to differences in interpretation based on dynamism and visual variables. Participants in the dynamic condition are more granular in some of their identification of different movement parameters, most often for counting the number of stops in movement. This suggests that dynamic displays can better communicate fine-grained speed changes. It also suggests that stops are more salient in dynamic visualizations than in static visualizations. Identification of major changes in direction does not differ, however, between static and dynamic conditions, suggesting that the overall path shape of the movement track is not noticeably different based on display condition. For movement, it seems intuitive that the representation of movement speed can be expressed more directly through animated trajectory lines and/or points in the display, rather than relying upon the participant to mentally translate speed information from another visual characteristic like color.

For comparisons of movement between two tracks, participants perform similarly well across static and dynamic conditions in assessing comparative movement speed, distance, range, and area of coverage. With relation to the framework of human-centered knowledge discovery from movement data, it appears that these location aspects are relatively easy for users to interpret in both static and animated forms. However, in this study, we only ask users to make a comparison between individual animals' tracks and do not assess user interpretations of interaction between the animals, which would potentially be better supported in the animated form (as it would point to co-incidence in both space and time, and leave it ambiguous in the static form).

In the open-ended descriptions of the track segments, we note differences in participants' level of agreement and use of terms related to movement direction and speed. By looking at frequencies of term usage in these descriptions, we find that participants make more mentions of direction for line-based visualizations and more mentions of speed for point-based visualizations. Participants in the study express a general preference for line-based designs over point-based visualization designs, with fewer positive rankings of point-based designs. However, it is worth noting that a preference for the line-based visualizations is likely to relate to prior familiarity for those types of designs depicting movement, which we did not assess in the study. Considering that movement tracks and routes are often depicted with a fixed-width line visualization in popular map applications like Google or Apple Maps, it is likely that familiarity is higher with line-based designs over point-based designs.

5.2. Limitations of the work and next steps for evaluation

This study mainly focused on the two-dimensional maps and displays. Future studies should consider comparisons of human interpretation across two-dimensional (2D) and three-dimensional (3D) movement visualizations, as well as including comparisons of movement visualizations that incorporate environmental variables. In general, users are likely to have greater familiarity with the use of static maps over dynamic maps, which may have hindered the performance of those participants in the dynamic condition. Future studies comparing static and dynamic maps or visualizations should include a short tutorial or examples to ensure that participants are familiar with the display form type beforehand.

We recognize more need to assess the level of complexity and realism that is most appropriate for geovisualization displays, such as through the addition of contextual information, and indeed user preference and efficiency or effectiveness may not always align (Hegarty et al., 2012). Although in the present study we attempt to capture more realistic movement visualizations with geographic context, the underlying basemap in this study is very simple and unlikely to introduce much complexity, therefore not competing for visual attention. Future studies should consider the impact of map design, as the geographic context influencing movement. Additionally, interaction with map and geovisualization displays is an important area of further work in the cognition of movement visualization. Interaction with map displays provides ample opportunity for exploratory analysis of geographic movement data in context.

These results are a significant step toward analyzing elements within the previously proposed framework for evaluating approaches to mapping movement (Dodge & Noi, 2021). The web-based study design has advantages such as the potential to quickly reach and scale to a broader pool of users, the allowance for maximum flexibility in study completion, and greater validity with regard to transferable use cases for web map visualizations (Griffin et al., 2017); however, there are trade-offs in being able to administer the study in a controlled display resolution and size. Although our participant descriptions of movement pointed to possible differences in the salience of movement characteristics, description of movement tracks may also be automatically processed using machine learning methods in the future (e.g. Pezanowski et al., 2022).

Considering the relative lack of prior research in the cognitive evaluation of geovisualizations of movement, it is important that we start with basic aspects of the evaluation framework, as we have presented here, and move onto introducing multifaceted geographic context information, including environmental variables, and more complex interaction capabilities in future work. Future studies would also benefit from having a control condition by including a design in which movement parameters such as speed, for instance, is not encoded through the visual variables.

6. Conclusion

This paper presented an empirical study using web-based surveys to evaluate the efficacy of various visual variables in capturing movement parameters along trajectories, such as speed and direction, using static and dynamic displays. As a result, this study made an important contribution toward the assessment of static and dynamic display forms for movement visualizations, and additionally highlighted the differences in and preferences for using size and color to represent movement speed in such displays. Both static and dynamic display forms supported participants' efficient and accurate interpretation of movement speed and direction and basic comparison tasks in this study. However, identification tasks suggested that dynamic display forms for movement tracks may support more fine-grained attention to pauses in movement, whereas static displays may support the identification of *changes* in speed. Participants also showed a strong preference overall for the line-based visualization designs over the point-based ones. For future studies, more specific interpretation tasks can further elucidate how well users can assess more complex movement trajectories, understand behavioral patterns, or understand visualizations of aggregated movement versus individual trajectories of movement.

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Author contributions

This research was conceived and led by SD as the PI. CB and SD designed the study and wrote the paper collaboratively. CB conducted the experiments, analyzed the results, and prepared figures.

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Data availability statement

The figures that support the findings of this study are available for viewing at https://doi.org/10.25349/D9BC9V.

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