Effect of Visualization Training on Uncertain Spatial Trajectory Predictions

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Objective: The goal of this study was to explore the ways in which visualizations influence the prediction of uncertain spatial trajectories (e.g., the unknown path of a downed aircraft or future path of a hurricane) and participant overconfidence in such prediction.

Background: Previous research indicated that spatial predictions of uncertain trajectories are challenging and are often associated with overconfidence. Introducing a visualization aid during training may improve the understanding of uncertainty and reduce overconfidence.

Method: Two experiments asked participants to predict the location of various trajectories at a future time. Mean and variance estimates were compared for participants who were provided with a visualization and those who were not.

Results: In Experiment 1, participants exhibited less error in mean estimations when a linear visualization was present but performed worse than controls once the visualization was removed. Similar results were shown in Experiment 2, with a nonlinear visualization. However, in both experiments, participants who were provided with a visualization did not retain any advantage in their variance estimations once the visualization was removed.

Conclusions: Visualizations may support spatial predictions under uncertainty, but they are associated with benefits and costs for the underlying knowledge being developed.

Application: Visualizations have the potential to influence how people make spatial predictions in the presence of uncertainty. Properly designed and implemented visualizations may help mitigate the cognitive biases related to such predictions.

Keywords: decision making, cognition, metacognition, visual displays, transfer of training

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INTRODUCTION

There are many instances in which people interact with spatial uncertainty in the world and must make spatial predictions in a state of future uncertainty—as in the case, for example, of locating a downed aircraft based on its trajectory over the ocean before contact was lost. In addition, estimating a target or an object's path and future location might involve making multiple predictions. For instance, the trajectory of a hurricane includes predicting when, where, and how intensely it will make landfall. The current research focuses on the effect of visualizations on continuous spatial predictions in the presence of uncertainty.

Across numerous domains, research has shown that prediction and forecasting are challenging tasks, even for experts, and often result in overconfidence in one's predictions and/or forecasts (Einhorn & Hogarth, 1982; Fischhoff & MacGregor, 1982; Regnier & Kirlik, 2012; Wickens, Hollands, Banbury, & Parasuraman, 2013). Forecasts of future behaviors, for a variety of reasons, may be inaccurate and thus inherently include elements of uncertainty (Wickens et al., 2013). People experience uncertainty when they lack the precise knowledge about the likelihood of events, which is a result of the probabilistic nature of the world (Lipshitz & Strauss, 1997). For weather forecasts, the uncertainty and underestimation of the impact of variable forces in the environment (i.e., forces acting upon the target and/or system) can lead to overconfidence in decision making (Kahneman, 2011; Regnier & Kirlik, 2012; Wickens, Gempler, & Morphew, 2000). People's confidence often exceeds their accuracy, and such overconfidence can affect the extent to which people plan for alternative actions (Wickens et al., 2013), such as evacuations in advance of a hurricane (Wu, Lindell, & Prater, 2015). One of the challenges with spatial trajectory predictions, such as storm-track forecasts, is that they require an estimation of a target's position in the future, when there is uncertainty about its characteristics (e.g., predicting a hurricane's landfall based on wind speed and direction).

Two experiments conducted by Herdener, Wickens, Clegg, and Smith (2016) explored the prediction of uncertain continuous spatial trajectories and the role of overconfidence in such predictions. The experiments specifically assessed two aspects of such predictions over time, to include a "typical" hurricane path (e.g., the most likely point and time of landfall) and the uncertainty itself (e.g., the variability, given the history of past tracks). Participants were shown multiple instances of a typical track and then asked to make predictions about the location of various trajectories at a future time. By measuring both aspects, they were able to evaluate how well individuals understand and estimate the path mean versus path variance of spatial trajectories. Their findings indicated that participants misrepresented the variance in predicting target location. In particular, they consistently estimated variance to be significantly less than it actually was, as if exhibiting overconfidence in the accuracy of their prediction. Subsequent studies replicated this overconfidence expression of poorly understood variance (Herdener et al., 2016; Wickens, Herdener, Clegg, & Smith, 2016; Wickens, Smith, Clegg, & Herdener, 2017). Additionally, their results indicated that people predicted linear paths with greater accuracy than curvilinear, accelerating paths and were particularly poor at estimating variability. They also found that participants were better in heading predictions than in speed predictions (Herdener et al., 2016). Given the challenges of predicting the growth of uncertainty, these studies suggest the need for remedies in understanding, of which two generic classes are training and visualization. Our research addresses the possible role of visualizations in increasing the accuracy of such prediction by supporting the understanding of the mean and the variance.

A common visualization utilized for hurricane forecasts is the "cone of uncertainty" hurricane track, which uses historical forecast errors to represent a 67% likelihood region for the actual hurricane track (Cox, House, & Lindell,

Figure 1. Graphical depiction of a hurricane cone of uncertainty. The solid white area represents the average forecast error. From the National Weather Service (2005).

2012; Regnier & Harr, 2006). The cone's vertex represents the current location of the storm's center at the time of the forecast and widens as the average error becomes larger (Broad, Leiserowitz, Weinkle, & Steketee, 2007). Thus, the width of the cone represents the likelihood region and serves an estimate of the uncertainty in the prediction (Liu, Mirzangar, Kirby, Whitaker, & House, 2015). The intent of the cone of uncertainty is to provide weather information so that those who are potentially affected can make timely and responsible decisions (Broad et al., 2007).

Despite being the primary visual aid for hurricane forecasts, previous research has indicated that most people misinterpret the concepts of probability and uncertainty being expressed in weather forecasts in general (Gigerenzer, Hertwig, van den Broek, Fasolo, & Katsikopoulos, 2005; Joslyn, Nadav-Greenberg, & Nichols, 2009), specifically by the cone of uncertainty, and place undue confidence in and attentional focus on the most expected forecast track of the storm (i.e., the center of the cone, or the black line shown in Figure 1; Broad et al., 2007; Cox et al., 2012). A common misinterpretation is that the areas located outside the edges of the cone are completely safe (i.e., poor understanding of the probability, since 33% of the forecast tracks will be outside the cone). This often results in an inappropriate overconfidence that the hurricane will pass through the areas within the cone and in a misunderstanding of the nature of the cone and the predicted trajectory (Cox et al., 2012).

A recent study of typhoon forecasters (Regnier & Kirlik, 2012) suggested that their forecast accuracy and consistency are likely to be negatively affected by technological and cognitive limitations that may manifest when they attempt to cognitively integrate an array of spatially oriented data. To address this issue, Regnier and Kirlik (2012) recommended the implementation of integrated information displays (i.e., visualization) that provide the validity or certainty level of weather data.

Ample research has documented the success of display visualizations assisting users in predicting individual trajectories in such domains as flight path prediction (Jensen, 1981; Wickens et al., 2000) and process control variable prediction (Roth & Woods, 1988; Yin, Wickens, Helander, & Laberge, 2015). Correspondingly, some research demonstrated the benefits of uncertainty visualization to human performance in decision, judgment, and estimation tasks (e.g., Andre & Cutler, 1998; Brolese & Huf, 2006; Finger & Bisantz, 2002; Riveiro, Helldin, Falkman, & Lebram, 2014; for a comprehensive review, see Bisantz, 2013).

As specific examples, Kirschenbaum and Arruda (1994) showed that a graphical uncertainty aid improved accuracy in moderately to highly difficult submarine location scenarios when compared with a verbal indicator of uncertainty. With a similar submarine sonar localization task, Kirschenbaum, Trafton, Schunn, and Trickett (2014) assessed the impact of uncertainty display format and showed that nonexpert operator performance was more accurate and quicker when uncertainty was displayed in a spatial instead of a tabular format. Thus, general findings suggest that the addition of uncertainty visualizations to displays may help users better understand the associated data and appropriately act upon it (Skeels, Lee, Smith, & Robertson, 2008) through the creation of mental models of integrated data (MacEachren, 1992). It is noteworthy that the aforementioned studies all examined visualization of uncertainty in the present state.

Whereas visualization has been documented to assist prediction of the mean or expected trajectory and although visualization of uncertainty has been documented to assist in the perception and use of uncertain information regarding the current state (i.e., diagnosis), there appears to be almost no research documenting the value of visualization of future uncertainty on performance. As one example of such research, Wickens et al. (2000) examined the potential benefits of a wedge uncertainty cone, like the cone of uncertainty in hurricane forecasting, to air traffic prediction of aircraft conflicts. The predictor line itself both increased performance and reduced workload. The addition of the wedge visualization provided no benefit to performance but did further reduce workload. More recently, Ruginski et al. (2016) conducted an experiment in which they measured the intuitive nature of five hurricane forecast visualizations by asking participants to rate the amount of damage predicted to occur at a given location. Our interpretation of their results indicates that individuals interpret hurricane forecast uncertainty differently according to the presented visualization (e.g., interpretation of hurricane size, intensity, and growth) and that the presence of a centerline and/or finite boundaries (i.e., cone outline) induce cognitive tunneling and monopolize attentional resources from focusing on the variability and uncertainty in the presented data. Although the Ruginski et al. study showed that individuals have different and, in some cases, better interpretations of various uncertainty visualizations, it did not measure the impact of each visualization on trajectory predictions. Thus, our research is designed to reduce the gap that exists at the intersection between uncertainty visualization and prediction visualization.

To further evaluate if a visualization can improve the ability to understand uncertainty and make spatial predictions, the current study duplicates the Herdener et al. (2016) experiments and includes the implementation of a predictive display in the form of a modified cone-of-uncertainty visualization. The design of the modified cone of uncertainty relied on guidance offered by Bisantz (2013) and MacEachren et al. (2012), with empirical results of Merwin and Wickens (1993) and Merwin, Vincow, and Wickens (1994), to represent uncertainty by a grayscale continuum, in which darker shades represent trajectory forecasts of greater certainty of predicted likelihood. Thus, rather than the single black line shown in Figure 1, there is now a continuum of decreasing saturation from the center to the boundaries of the cone.

As with the previous Herdener et al. (2016) experiments, the current studies assessed the differences in the prediction of central tendency and variance of spatial trajectories, as well as the differences in predictions of speed and direction. Building on and extending the previous results that examined performance only, the current study explored the effects of learning/training on the use of visualization to aid the understanding of predictive uncertainty. We did this in a transfer-of-training design. Participants in an experimental group were provided with the visualization during a training phase, which was then removed during a transfer phase to evaluate if a transfer-of-training effect existed. Their transfer performance was compared with that of a control group, which never saw a visualization during training.

The rationale for evaluating visualization in a transfer-of-training paradigm is twofold. First, we are interested in whether visualization of uncertainty can impose any gain in long-term knowledge or cognitive skills relative to the understanding of uncertainty that would sustain even when the tool was removed, in a manner that has rarely been examined in visualization research and never in terms of research on visualization of uncertainty. Some pessimism that this may be possible was provided by Kahneman (2011), whose conclusions suggested that biases of overconfidence (i.e., the commodity expressed in our evaluation of uncertainty expression) are extremely resistant to training. Second, an opposing force to gaining knowledge of uncertainty that would transfer is the possibility that providing visualization during training could lead to some dependency on the visualization producing an effect (not unlike that observed in human-automation interaction) such that when the visualization (or automation) is suddenly removed, performance is actually worse than it is without any visualization at all.

A limitation relevant to the existing research is whether visualizations can increase the understanding of uncertainty in a way that transfers when the visualization is withdrawn. Many visualizations were shown to assist the operator in a task while they are present but offer little to no value once removed (Wickens, Merwin, & Lin, 1994). Furthermore, in some cases, the removal of the visualization may even degrade performance relative to a nonvisualization baseline if users had become dependent on them. One example of this latter effect is provided by Smith (2008), who showed that novices who trained on flight skills with a functional aviation display and then transferred to a conventional display without graphic visualizations demonstrated decreased knowledge and performance relative to a control group that had not received such visualization. Smith's study did not, however, examine visualization of uncertainty.

Indeed, some evidence that this dependency effect might not be observed is provided by a meta-analysis of skill training strategies carried out by Hutchins, Wickens, Carolan, and Cumming (2013). They found that the strategies of "training wheels" and scaffolding generally transferred positively to performance when they were removed. However, there was considerable variance across studies in this positive transfer effect, and none of the studies involved a visualization of uncertainty as a strategy (nor understanding of uncertainty as a target skill to be trained).

Hence, the central focus of our current study aimed to empirically evaluate the effectiveness of an uncertainty visualization tool in performance and learning, by employing a transfer phase to evaluate the impact of the visualization on unaided posttraining spatial predictions. Building on the original research paradigm and design employed in the Herdener et al. (2016) study, we developed a modified cone-of-uncertainty visualization that incorporated grayscale gradient shading to represent the probabilistic nature of the predicted trajectory mean and variance.

In a transfer-of-training design, participants in two experiments were given the opportunity to learn the speed and direction of an object moving on a map. By providing the participants with several encounters or samples of a trajectory's model behavior, it is expected that they will learn the trajectory's mean path and be able to predict the location of the object at a future time, T_3 (i.e., a look-ahead time of two time units). Additionally, after viewing these several samples consecutively, participants were asked to estimate the probability that the object would be located in a sampling of various regions at T_3. In doing so, we were able to evaluate their understanding of the trajectory's variance or the growth of uncertainty, based on their experience of multiple trajectories following the same general path, similar to the history of hurricanes arriving to the Gulf Coast. Experiment 1 employs linear trajectories, whereas Experiment 2 involves trajectories that accelerate in speed and heading (i.e., curvilinear). These trajectories correspond to Experiments 1 and 2 of Herdener et al. (2016), respectively.

Participants randomly assigned to the experimental (visualization) group were provided with the cone visualization during a training phase; then, the visualization was removed during a transfer phase to assess any transfer-of-training effects that may have occurred. Participants in the control group made the same forecasts on the same trajectories during the training phase but were never provided with visualizations.

EXPERIMENT 1

Based on the existing literature and the results from the Herdener et al. (2016) study, three hypotheses are offered for Experiment 1:

Hypothesis 1.1: When a cone-of-uncertainty visualization is presented during training, participants will have less error in their estimations of the target's trajectory mean and variance when compared with those not presented with a visualization.

Hypothesis 1.2: To the extent that the cone-of-uncertainty visualization facilitates learning (understanding variance) as well as prediction performance before it is removed during the transfer phase, participants will have better variance estimation prediction (less overconfidence) in their estimations of the target's trajectory as compared with those in the control group, who are not presented with a visualization.

Hypothesis 1.3: On the basis of the earlier findings of Herdener et al. (2016), participants will be better at extrapolating trajectory heading than distance.

Method

Participants. The experiment included 88 participants receiving optional partial college course credit. Participants were randomly placed in the control or experimental group (i.e., visualization group) for a between-subjects design. This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Board at Colorado State University. Informed consent was obtained from each participant.

Task and procedure. The experiment was administered with the E-Prime software platform. Participants were asked to complete seven two-phase blocks: six experimental blocks and one practice block. The practice block comprised 16 total trials (8 per phase), and each experimental block included 32 trials (16 per phase). For the first phase of each block, which was designed to assess performance in projecting the mean, participants were shown a sequence of instances of a target trajectory distribution to allow them to learn the underlying pattern, or "model," and experience the variability underlying that model. In the second phase, which was designed to assess their knowledge of uncertainty or variance, participants were shown a probe circle on each trial and asked to estimate the probability that the target was within the probe circle.

Each of the six blocks included a distribution of target trajectories drawn from the same mean direction and speed/distance traveled for both phases, with a different distribution used for each block (Figure 2A). Based on this model, a trajectory from time T_0 to T_3 was calculated. Normal Gaussian distributions were used to add randomized variance to both speed and direction. Different trials then created a distribution of trajectories centered on a model (Figure 2B). The starting-point location and azimuth of each target varied around the edges of the screen between blocks so that no two blocks displayed the same trajectory. Additionally, the order in which the different models were presented to participants was randomized within the first four blocks (i.e., training blocks) and within the last two blocks (i.e., transfer blocks).

Participants in the control group viewed only one sample at a time and never viewed a

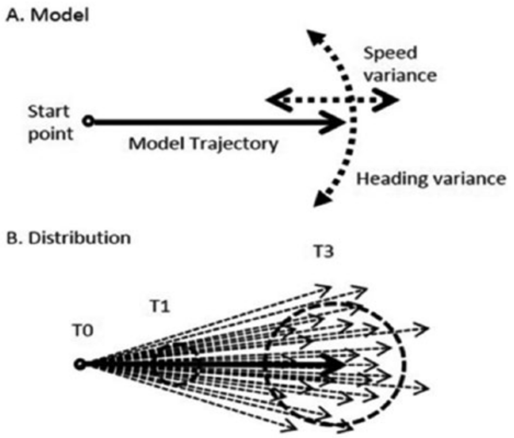

Figure 2. Schematic of underlying target behavior: (A) model and (B) distribution of trajectories. From Herdener, Wickens, Clegg, and Smith (2016).

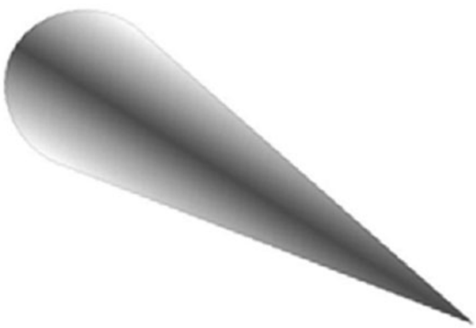

Figure 3. Cone visualization. An example of the grayscale gradient visualizations used to depict likely trajectory and variance.

representation of the data collectively. However, participants in the experimental group (i.e., visualization group) were shown a cone visualization (Figure 3) underlay during Phase 1 of the first four blocks (i.e., training blocks). The visualization was removed during Phase 1 of the last two blocks (i.e., transfer blocks) to assess if there was a transfer-of-training effect. The visualization cone was sized, positioned, and shaded to capture approximately 68% of all the trajectories in each block to align with the standard likelihood region of 67% used by the National Hurricane Center (Cox et al., 2012).

At time T_1, a possible location of the target was randomly selected from the distribution of samples to be shown to the participant. Each training trial consisted of four consecutive screens (Figure 4). Participants in the visualization group were provided with the visualization underlay only during Phase 1 of the training blocks. For the last two transfer blocks, participants in the control and visualization groups were both shown the same screens without a visualization aid. Screen 1 showed the location of the target at time T_0 (i.e., starting point) at a set point along the horizontal and vertical edge of the screen for 5 seconds. Screen 2 showed a possible location of the target at T_1 but was taken from a different sample of the same model in an attempt to prevent simple extrapolation. To induce uncertainty and reduce the chance of extrapolation, participants were informed that the location of the target at T_1 was a possible location and not necessarily the true location.

Screen 3 was identical to Screen 2 except that it included a prompt instructing the participant to estimate the target location at T_3 (i.e., twice the time interval and distance traveled from T_0 to T_1). The participant then used the computer mouse to place a crosshair on his or her estimated location of the target. Screen 4 provided the participant feedback by showing the true location of the target at T_0, the model target location of the target at T_1, his or her target location estimation, and the true target location calculated by the sampled trajectory for T_3.

Participants were also given a numerical calculation of the error distance between the prediction crosshair and the location of the target (e.g., “Distance: 40”). Screen 4 was shown for 10 seconds before a new trial began with a new sample trajectory calculated from the same model and variance. Upon completion of 16 trials in Phase 1, participants advanced to Phase 2. For each block, a new model was generated, which changed the direction of the vector, the distance moved, and the splay of the vectors (i.e., the growth of uncertainty).

Phase 2 of each block consisted of 16 trials, and each phase included two screens presented in sequential order. Screen 1 was identical to Screen 1 shown in Phase 1. However, Screen 2 presented a 100-pixel-diameter circle at a point selected from a grid pattern centered on the model trajectory at T_3. Participants were asked

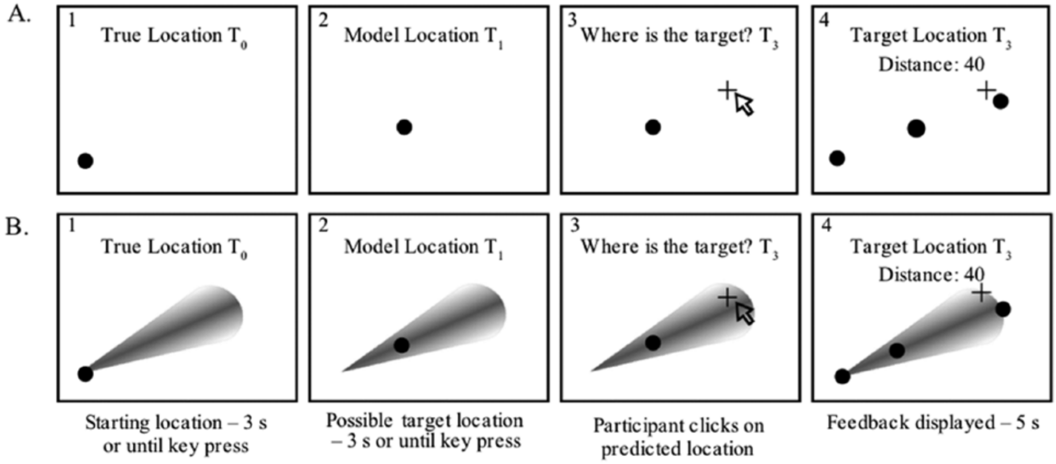

Figure 4. Schematics of Phase 1 sequence. The schematic in Panel A is shown to the control group. Panel B illustrates the schematic with the visualization aid shown to the experimental/visualization group. Each panel depicts one of the 16 trajectories shown on a block of trials.

to input a percentage estimate of the probability that the target was within the presented circle. The estimation provided a subjective perceived confidence interval that corresponded with the percentage response given by the participant. The center of each circle was presented randomly from a grid pattern of locations centered on the two-dimensional model mean endpoint (i.e., the center of the distribution for the given model). Locations closer to the center of the distribution were more likely to be presented. Screen 2 remained visible until the participant responded and then a new trial began. Feedback was not provided during Phase 2, to prevent continued learning of the target behavior after Phase 1. This procedure was repeated for 16 trials before a new block of trials began, with Phase 1 containing a new model.

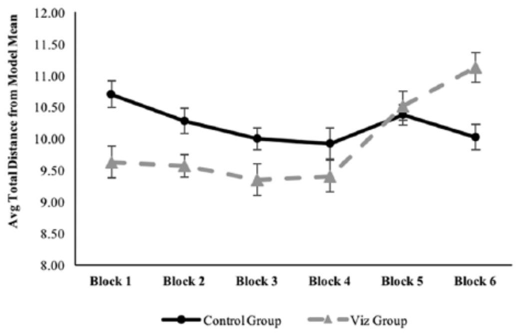

Figure 5. Experiment 1, Phase 1 (mean estimation), results. Average total distance (in pixels) between the participants' predicted locations and the model mean across trials. The error bars represent 1 *SE*.

Results

Phase 1: Prediction of mean trajectory. Accuracy for Phase 1 was measured by calculating the absolute distance between the participant's predicted location at T_3 and the model mean for each trial. The average absolute distance across trials was calculated for each block for the control group and the visualization group. A square root log transformation was performed to correct for positive skew in the data. The transformed data are depicted in Figure 5.

Analysis of the Phase 1 results (i.e., prediction of the mean) examined performance in the four training blocks. A 2 × 4 (Group × Block) analysis of variance (ANOVA) revealed a significant advantage for the visualization group, $F(1, 86) = 11.58$, $p < .005$, $\eta^2 = .12$. There was a significant main effect for block (i.e., Block Order 1–4), reflecting learning, $F(3, 258) = 3.37$, $p < .05$, $\eta^2 = .04$, but no significant interaction.

The two transfer blocks (5 and 6) in which the visualization was removed for the visualization group were analyzed with a 2 × 2 (Group × Block) ANOVA. The analysis revealed a main effect for group that, in contrast to the training blocks, favored the control group, $F(1, 86) = 6.39$, $p < .05$, $\eta^2 = .07$, no effect of block, $F(1, 86) = 0.61$, $p = .44$, $\eta^2 = .01$, and a significant Group × Block interaction, $F(1, 86) = 8.73$, $p < .01$, $\eta^2 = .09$. There was no effect of group on Block 5, but on Block 6 the control group performed significantly better ($M = 10.02$, $SE = 0.11$) than the visualization group ($M = 11.12$, $SE = 0.13$), $t(1,406) = –6.28$, $p < .001$, $d = 0.33$.

As hypothesized (H1.3), error was greater for distance than for heading, $t(87) = 43.23$, $p < .001$, $d = 3.85$ (along track [distance], $M = 234$ pixels, $SE = 2.69$; across track [heading], $M = 147$ pixels, $SE = 2.08$).

Phase 2: Prediction of variance. In Phase 2, participant estimates of the probability that the target was located within the presented circle probes were compared with the distribution of endpoints generated by 10,000 simulations of the model. Consistent with the study results of Herdener et al. (2016), participants were quite erroneous in their predictions of the model variance. On average across all trials, participants from both the visualization group and the control group overestimated the probability by 39.4% (i.e., the estimated probability error minus the model simulation error). We can refer to this as a 39.4% overconfidence in the accuracy of their mean estimate.

As in Phase 1 (mean estimation), the average overestimation of probability across Phase 2 (variance estimation) trials was further analyzed separately for the training and transfer block trials. Figure 6 displays the results of this analysis in the same format as for the error data in Figure 5.

The training block data for variance were analyzed by a 2 × 4 (Group × Block) ANOVA, which revealed no significant effect for group, $F(1, 86) = 0.24$, $p = .63$, $\eta^2 = .003$, or block, $F(3, 258) = 0.90$, $p = .44$, $\eta^2 = .01$, but a significant Group × Block interaction, $F(3, 258) = 2.72$, $p < .05$, $\eta^2 = .03$.

The two transfer blocks were again analyzed with a 2 × 2 (Group × Block) ANOVA, which revealed no significant effect for group, $F(1, 86) = 1.04$, $p = .31$, $\eta^2 = .01$, block, $F(1, 86) = 0.76$, $p = .39$, $\eta^2 = .009$, or interaction, $F(1, 86) = 0.06$, $p = .80$, $\eta^2 = .00$. There was a small effect of a greater improvement over trials for the visualization group but no overall benefit of visualization in training. Thus, in summary, visualization benefited estimation of the mean when present, but no such benefit was exhibited for variance estimation.

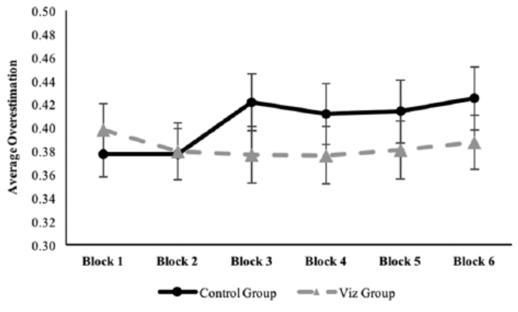

Figure 6. Experiment 1, Phase 2 (variance estimation), analysis results. Average overestimation of probe probability between control group and visualization group. Error bars represent 1 *SE*.

Discussion

For Experiment 1, we proposed three hypotheses regarding the benefits of visualization to prediction performance and, particularly, the improved calibration of uncertainty (reduction in overconfidence) in extrapolating two-dimensional trajectories for heading and relative to speed (i.e., distance/time).

For H1.1, we predicted that a cone visualization with an overlaid set of predicted paths would improve (relative to a control condition) the accuracy of prediction and, more important, the understanding (calibration) of predicted variability. Such a cone not only expressed anticipated variability by its outer edges but conveyed additional uncertainty by a grayscale gradient that approximated the normal distribution of trajectories. This hypothesis was confirmed for mean and variance estimation, although considerable underestimation of variance, interpreted as overconfidence (38%), remained and the reduction in overconfidence provided by the visualization cone was not strong.

For H1.2, we examined the possible transfer benefits of the cone visualization by examining performance on variance estimations when the visualization was removed. Here we found that such an advantage for variance estimation did not remain during transfer, disconfirming H1.2. The results showed an effect that was more like the "dependency" described in the introduction for the mean and a null effect for variance, as if the effect of dependency was offset by some learning. It is possible that the dependency effect for the mean could be attributed to participants' "crutch-like" dependence on the dark band that defined the centroid of the visualization cone (Figures 1 and 3).

H1.3 contrasted the greater difficulty of distance than heading extrapolation, and our findings here replicated the findings of Herdener et al. (2016).

These results continued to demonstrate an important cognitive challenge in the abstract version of this important real-world task (linear trajectory extrapolation), particularly related to an inadequate cognitive representation of uncertainty. Although participants in both conditions were capable of learning the average behavior of a spatial trajectory, they remained relatively insensitive to the trajectory's variance. For both variables, the visualization cone helped when present but not when removed.

EXPERIMENT 2

Whereas Experiment 1 involved linear trajectories with normal Gaussian distributions to add randomized variance to speed and direction, Experiment 2 explored the same prediction tasks with more complex trajectory behavior. The introduction of more complex curvilinear trajectories was done, in part, because previous research showed that people are considerably worse at extrapolating nonlinear trends (Herdener et al., 2016; Wickens et al., 2013). Additionally, curvilinear trajectories better represent the unpredictable nature of many real-world trajectories, such as hurricanes. Figure 7 is an alternative graphical depiction to the cone of uncertainty (Figure 1), reflecting the nonlinear heading trend and referred to as a *spaghetti plot*. This graphic represents a hurricane path's inherent uncertainty through the ensemble of trajectory predictions based on different weather models (Toet, Tak, & Van Erp, 2016). As with the second experiment in the Herdener et al. (2016) study, Experiment 2 manipulated heading by curving the target trajectory path. Speed

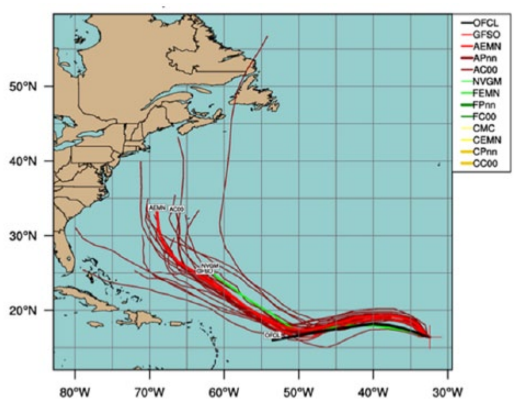

Figure 7. Hurricane spaghetti plot. From the National Center for Atmospheric Research (2017).

was manipulated by adding either acceleration or deceleration to the target so that it either sped up or slowed as time progressed and reflected the information necessary to predict the time of landfall. With such manipulations, Herdener et al. demonstrated that participants had greater difficulty predicting the mean and estimating the variance of curvilinear trajectories compared with linear trajectories. In Experiment 2, we explored whether visualization could help offset these greater limitations in both training and transfer.

The Herdener et al. (2016) study included three manipulations to target behavior: heading change (curved path) only, speed change (acceleration) only, and heading and speed change combination. Their results indicated that the heading and speed change combination was more difficult (i.e., harder to predict the mean trajectory) than the single-dimension judgments (e.g., judgments for trajectories with only a change in acceleration were easier than judgments for trajectories that included a curve and acceleration change). Since the goal of the current study is to evaluate how visualizations influence such trajectory predictions, Experiment 2 incorporated only the most difficult condition (i.e., nonlinear heading and speed changes combined).

We expected to find results in support of the Herdener et al. (2016) study in that manipulations to the curvature and acceleration of a target trajectory would increase the difficulty in

TABLE 1: Speed and Direction Parameter Changes for Trajectory Behavior in Experiment 2

Phase: Block	Curvature	Change in Speed
Training		
1	10°, slight curve	10 pixels, slow acceleration
2	30°, sharp curve	10 pixels, slow acceleration
3	30°, sharp curve	30 pixels, fast acceleration
4	10°, slight curve	–10 pixels, slow deceleration
Transfer		
5	30°, sharp curve	–10 pixels, slow deceleration
6	10°, slight curve	10 pixels, slow acceleration

predicting the future locations of the target. Thus, Experiment 2 posed the following hypotheses:

Hypothesis 2.1: Overall prediction performance will be poorer than in Experiment 1 for the control group.

Hypothesis 2.2: When a cone-of-uncertainty visualization is presented during training, participants will have less error in their estimations of the target's trajectory mean (Phase 1) and variance (Phase 2) as compared with those not presented with a visualization. This reduction in variance estimation error would be in the direction of reducing overconfidence.

Hypothesis 2.3: The third hypothesis, regarding possible transfer benefits of the cone was less well defined given the results from Experiment 1 since we had originally hypothesized that the visualization would help variance estimation on transfer but found that it did not. On one hand, we might hypothesize the same null hypothesis here. On the other, given the established greater difficulty of the curvilinear accelerating predictions of the mean (to the detriment of variance focus), we anticipate that the advantages of visualization may be reduced, producing an actual cost (rather than just having no benefit).

Method

Participants. Experiment 2 included 97 participants receiving optional partial college course credit. Participants were randomly assigned in near-equal numbers to the control or experimental group (i.e., visualization group) for a between-subjects design.

Task and procedure. The experimental design for Experiment 2 was similar to that of Experiment 1 but included several differences in the model for the target trajectories. Models in Experiment 2 introduced additional terms corresponding to change in speed (i.e., acceleration) and change in direction (i.e., curvature of trajectory). The change in direction set the curve of the trajectory to change by 10° or 30° (i.e., slight vs. sharp curve) between T_n and T_{n+1}, whereas change in speed was set so that the target either accelerated or decelerated by 10 pixels or 30 pixels per time interval (i.e., slow or fast change) between T_n and T_{n+1}. Change in speed and direction varied by block. Table 1 outlines the speed and direction changes by block.

The procedure and screen sequence for the study remained the same as in Experiment 1 (Figure 4). Participants randomly assigned to the visualization group were presented with a gradient-shaded cone-of-uncertainty visualization (Figure 8) to reflect the underlying model distribution in the first four transfer blocks. The visualization was removed during the last two transfer blocks.

Results

Phase 1: Prediction of mean trajectory. As with Experiment 1, accuracy for Phase 1 was measured by calculating the absolute distance between the participant's predicted location at T_3 and the model mean for each trial. The average absolute distance across trials was

Figure 8. Experiment 2 cone visualization.

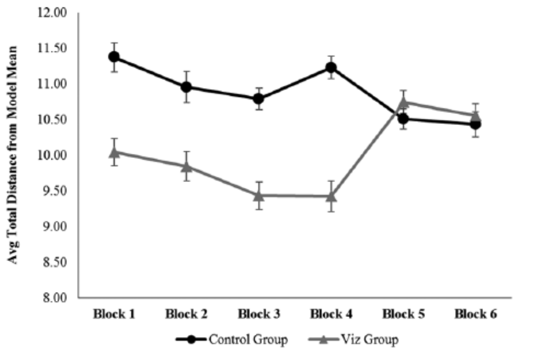

Figure 9. Experiment 2, Phase 1, results. Average total distance (in pixels) between the participant's predicted locations and the model mean across trials. The error bars represent 1 *SE*.

calculated for each block for both groups. A square root log transformation was performed on the data to correct for positive skew. The transformed data are depicted in Figure 9.

Analysis of the Phase 1 results (i.e., prediction of the mean) examined performance in the four training blocks. A 2 × 4 (Group × Block) mixed ANOVA revealed a significant advantage for the visualization group, $F(1, 95) = 23.98$, $p < .001$, $\eta^2 = .20$. Consistent with learning across blocks, there was a significant main effect for block (i.e., Block Order 1–4), $F(3, 285) = 6.32$, $p < .001$, $\eta^2 = .06$, but no significant interaction. Thus, these results replicated the findings of Experiment 1.

The two transfer blocks (5 and 6) were analyzed with a 2 × 2 (Group × Block) mixed

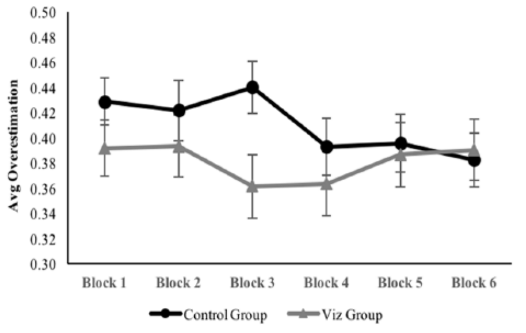

Figure 10. Experiment 2, Phase 2, analysis results. Average overestimation of probe probability between the control group and the visualization group. Error bars represent 1 *SE*.

ANOVA. The analysis revealed no significant effect for group, $F(1, 95) = 0.55$, $p = .46$, $\eta^2 = .01$, no effect for block, $F(1, 95) = 1.19$, $p = .28$, $\eta^2 = .01$, and no significant Group × Block interaction, $F(1, 95) = 0.00$, $p = .98$, $\eta^2 = .00$.

In comparing the results of Experiment 1 with those of Experiment 2, we performed a contrast between the control group data of the two experiments in a 2 × 6 (Experiment × Block) mixed ANOVA. These results revealed a significant main effect for experiment, $F(1, 91) = 10.48$, $p < .01$, $\eta^2 = .10$, with Experiment 2 exhibiting greater error in average mean estimation ($M = 10.88$, $SE = 0.14$) than in Experiment 1 ($M = 10.21$, $SE = 0.15$).

Phase 2: Prediction of variance. As with Experiment 1, in Phase 2, participant estimates of the probability that the target was located within the presented circle probes were compared with the distribution of endpoints generated by 10,000 simulations of the model. These overconfidence values are depicted in Figure 10. The average overestimation of probability across Phase 2 trials (approximately 40%) was further analyzed by trial type (training and transfer) and compared between participants in the two groups.

The training phase data for variance (overconfidence) were analyzed by a 2 × 4 (Group × Block) mixed ANOVA and revealed no significant effect for group, $F(1, 95) = 2.24$, $p = .14$, $\eta^2 = .023$, or a Group × Block interaction, $F(3, 285) = 1.95$, $p = .12$, $\eta^2 = .02$, and with small effect sizes associated with both. However, the results showed a significant effect for block, $F(3, 285) = 2.88$, $p < .05$, $\eta^2 = .03$. Across the training blocks, participants demonstrated a decrease in overconfidence.

The two transfer blocks were analyzed with a 2 × 2 (Group × Block) mixed ANOVA, which revealed no significant effect for group, $F(1, 95) = 0.00$, $p = .99$, $\eta^2 = .00$, or block, $F(1, 95) = 0.17$, $p = .68$, $\eta^2 = .002$. In comparing the results of training benefits on variance estimation between the two experiments, we performed a 2 × 6 (Experiment × Block) mixed ANOVA on the overconfidence measures, equivalent to that performed on the mean. The results revealed no significant difference between the two experiments, $F(1, 91) = 0.04$, $p = .84$, $\eta^2 = .00$.

Discussion

As mentioned previously, in Experiment 2 we expected to find results that further supported the findings of Herdener et al. (2016). By imposing acceleration (changes) in speed and heading of the target trajectory behavior, we anticipated that participants would have greater difficulty in predicting the future locations of the target than with the linear trajectories presented in Experiment 1. Based, in part, on the Herdener et al. results, we originally expected that overall prediction performance would be poorer than in Experiment 1 for the control and visualization groups. H2.1 contrasted the control group's average error between Experiment 1 and Experiment 2 and revealed that, indeed, participants in Experiment 1 exhibited less error in their mean estimations with linear trajectories than those in Experiment 2 with curvilinear accelerating trajectories.

For H2.2, we again examined the possible training aid benefits of the cone visualization by examining performance on the mean predictions and the understanding of predicted variability. Similar to Experiment 1, we predicted that a cone visualization with an overlaid set of predicted curvilinear paths would improve performance on both measures relative to the control group. We found this prediction was upheld for the estimations of the target's trajectory mean but not for the variance estimations. Presenting a visualization during the training phase did not significantly improve or worsen the participants' understanding of trajectory variance. However, results from the Phase 2 analysis showed that participants in both groups demonstrated decreased overconfidence across training blocks. This finding seems to indicate that participants are becoming more calibrated in their understanding of variance from Block 1 to Block 4.

Based on the findings from Experiment 1, we expected that the increased difficulty associated with curvilinear trajectories would result in participants having even greater overconfidence in their variance estimations (relative to the control group) once the visualization was removed in the transfer phase. The analysis results demonstrate neither an additional benefit nor a cost associated with the presence of a visualization during training.

GENERAL DISCUSSION

The data from both experiments can be examined by asking three major questions: How does prediction differ between the two experiments? How does the cone visualization assist participants when present during training for easy and hard predictions on mean and variance estimations? What is the effect of such training on skill transfer once the visualization is removed?

Regarding the first question (i.e., differences between experiments), we observe that, congruent with Herdener et al. (2016), the curved and accelerating trajectories in Experiment 2 are more difficult to predict than the linear trajectories used in Experiment 1. By examining the control group's performance, we find that prediction error is increased in training and transfer. In contrast, overconfidence did not differ significantly between the two experiments, as if the greater resource demands of curvilinear predictions did not withdraw resources from variance estimation. To help examine the second and third questions, the general trends of findings from both experiments are summarized in Table 2.

Regarding the second question (i.e., differences due to visualization in training), our results showed that the cone visualization clearly assisted participants during training. The visualization that we used in both experiments offered two separate pieces of information. The heavily shaded center of the cone was intended to assist in mean predictions, whereas the rest of the gradient-shaded cone was designed to assist in

TABLE 2: Summary of Results

	Training Phase	Transfer Phase
Experiment 1: Easier linear trajectories		
Mean estimation (error)	Viz reduces error	Viz increases error on Block 6
Variance estimation (overconfidence)	Viz reduces error on Blocks 3 and 4	Viz does not improve/worsen performance
Experiment 2: Harder accelerating trajectories		
Mean estimation (error)	Viz reduces error	Viz does not improve/worsen performance
Variance estimation (overconfidence)	Viz does not improve/worsen performance	Viz does not improve/worsen performance

Note. viz = visualization.

variance estimations. The visualization assisted mean prediction and variance estimation. In Experiment 1, the visualization offered a significant benefit for mean prediction during the training phase and for variance estimation during the last two training blocks (i.e., Blocks 3 and 4). For the more difficult predictions in Experiment 2, the visualization offered a much larger benefit for mean prediction. This benefit was almost double the benefit found in Experiment 1. However, the visualization offered no benefit for overconfidence calibration (i.e., variance estimation).

Contrasting mean prediction and variance estimation, we find some evidence that when visualization helped one judgment more, it helped the other one less. This reciprocity suggests that the information processing required to make the two estimations was competing for limited attentional resources. That is, during Phase 1, the explicit concentration on estimating the mean trajectory (called for by task instructions) competed with any implicit learning of the variability. Specifically, in Experiment 1, the benefit of visualization on mean prediction was less, whereas the benefit for variance estimation or overconfidence reduction was more; however, in Experiment 2, the benefit of visualization for mean estimation was doubled, and the benefit for variance learning (overconfidence reduction) was entirely eliminated. This finding is consistent with the idea of an attentional focus tradeoff on the two visualization attributes. That is, attentional focus is likely distributed more equally between mean estimation and variance learning in Experiment 1 but allocated more intensely to only the trajectory's mean (i.e., heavily shaded center of cone) at the expense of implicitly learning the trajectory's variance (i.e., the remaining gradient-shaded portions of the cone) when that mean became more difficult to predict in Experiment 2. This finding replicates the more informal observations made by Broad et al. (2007) that those processing cones of uncertainty in hurricane prediction (often curved) pay excessive attention to the black line in the center at the expense of the cone's boundaries.

The third question (i.e., transfer effects) addresses the transfer effects of being exposed to visualization training. For such an evaluation, we consider the possible offsetting influence of the two hypothesized variables discussed in the introduction: learning, which would aid performance on transfer, and dependence, which would hurt it. For Experiment 1, we found a clear dependence effect for mean prediction. The visualization benefit that resulted in error reduction during training turned into a visualization cost of during transfer. With respect to overconfidence, the results were ambiguous and did not offer a clear effect. The benefits seen during training were eliminated during transfer. It is possible that a dependence effect similar to that found with mean prediction was offset by a learning effect of the same magnitude.

In Experiment 2, for the mean, an effect similar to that observed for variance (overconfidence) in Experiment 1 was observed. That is, the advantage of visualization during training disappeared during transfer. Finally, for overconfidence, in Experiment 2, there was again no effect (benefit or cost) to transfer of having been exposed to the visualization during training. However, there had been no visualization advantage for variance (overconfidence) during Experiment 2 training either, and this may suggest that with the more difficult nonlinear task, participants' attention had been solely focused on the mean (i.e., the heavily shaded center of the curved cone). Thus, neither dependency on (training) nor learning of (transfer) the cone's variance information itself developed in Experiment 2. This interpretation is supported by previously mentioned research indicating that most people misinterpret the cone of uncertainty and place undue confidence in and attentional focus on the most expected forecast track of the storm (i.e., the center of the cone; Broad et al., 2007; Cox et al., 2012). Such a finding of overconfidence might, for example, lead people to underprepare for trajectories toward the outer edge of the variability (e.g., in the case of hurricane forecasting, insufficient evacuation of those living on the outer edges of a cone of uncertainty).

Overall, across both experiments and both variables, visualization helped performance more when it was present (three of four effects were benefits) but harmed performance somewhat more when it was withdrawn (one of four effects was a benefit). Thus, the benefit of the grayscale shaded cone as a training tool appears minimal. Mitigation of the cognitive biases related to overconfidence with visualizations or other forms of instruction remains ambiguous, as both experiments examined only one form of visualization. We found that, in certain cases, visualization can create dependence and produce a crutch-like effect for users. Thus, if the intent behind a particular visualization is to serve as a performance aid and not a training aid, then it is critical to design a visualization that creates and/or enhances a transferable skill.

Applications, Practical Applications, Limitations, and Future Directions

The findings presented here show potential in improving how people make spatial predictions in the presence of uncertainty. This particular skill set and cognitive ability are applicable to not only weather forecasts but any strategic decisions that involve estimates of future spatial uncertainty (e.g., possible locations for a downed aircraft). The fact that we found performance improvements when visualization was present (i.e., during the training blocks) supports the continued development and implementation of such visualizations. These current experiments provided an important first step in exploring the transfer-of-training aspects of uncertainty visualizations.

Additionally, our findings provide further insight into the conditions under which people experience overconfidence when making predictions. Even when presented with an uncertainty visualization, people still exhibited greater attentional focus on the mean and overconfidence in their understanding of the variance. These results have implications for decision makers and the consequences related to not considering alternatives to the most likely outcome.

Although the results of this study are compelling, an important limitation of this research is its dependency on a relatively simple abstract task with naïve participants. Even as overconfidence is well demonstrated with experts (Kahneman, 2011; Tetlock, 2005) in other circumstances, there is a need to demonstrate biases and visualization mitigations on more realistic simulations of real-world spatial prediction tasks. Second, the current study tested only one type of visualization. With only one visualization design, the results are not fully generalizable. It is possible that different forms of visualizations may better enhance the understanding of variance, improve transfer effects, and reduce related overconfidence. In fact, Ruginski et al. (2016) found that the addition of a centerline, fuzzy shading, and/or ensemble paths to a cone visualization decreased the perception of variance. As such, our future research will incorporate visualizations similar to those used by Ruginski et al. to assess if the prediction of spatial trajectories is differently influenced by how each visualization is interpreted in terms of variance.

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KEY POINTS

- We examined the influence of a visualization on the prediction of uncertain spatial trajectories, such as the unknown path of a downed aircraft or the future path of a hurricane. Previous research indicated that people often misunderstand uncertainty and are overconfident with such predictions.
- In our first experiment, we found that, when present, a visualization helped reduce prediction error for linear trajectories. Once it was removed, those presented with a visualization retained no advantage for variance estimation (overconfidence).
- In our second experiment, we found mean prediction results similar to Experiment 1 for accelerating curvilinear trajectories. However, the visualization offered no benefit for overconfidence calibration.
- In both experiments, visualization helped performance more when it was present but harmed performance somewhat more when it was withdrawn. Visualizations may support spatial predictions under uncertainty, but they are associated with benefits and costs for the underlying knowledge being developed. We found that, in certain cases, visualization can create dependence and produce a crutch-like effect for users.

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