



1 **Understanding representations of uncertainty, an eye-tracking study part II: The effect**  
2 **of expertise**

3 Louis Williams<sup>1,4</sup>, Kelsey J. Mulder<sup>2</sup>, Andrew Charlton-Perez<sup>2</sup>, Matthew Lickiss<sup>3</sup>, Alison  
4 Black<sup>3</sup>, Rachel McCloy<sup>4</sup>, Eugene McSorley<sup>4</sup>, Joe Young<sup>5</sup>

5

6 <sup>1</sup>ICMA Centre, Henley Business School, University of Reading, Whiteknights, PO Box 242,  
7 Reading, RG6 6BA, United Kingdom.

8 <sup>2</sup>Department of Meteorology, Earley Gate, University of Reading, Whiteknights Road, PO  
9 Box 243, Reading, RG6 6BB, United Kingdom.

10 <sup>3</sup>Department of Typography & Graphic Communication, School of Arts, English and  
11 Communication Design, No. 2 Earley Gate, University of Reading, Whiteknights Road, PO  
12 Box 239, Reading RG6 6AU.

13 <sup>4</sup>School of Psychology and Clinical Language Sciences, Earley Gate, University of Reading,  
14 Whiteknights Road, PO Box 238, Reading, RG6 6AL, United Kingdom.

15 <sup>5</sup>Department of Atmospheric Sciences, University of Utah, 115, Salt Lake City, UT 84112,  
16 United States

17

18 Correspondence to: Louis Williams (louiswilliams@dynamicplanner.com)

19



20 **Abstract.** As the ability to make predictions of uncertainty information representing natural  
21 hazards increases, an important question for those designing and communicating hazard  
22 forecasts is how visualisations of uncertainty influence understanding amongst the intended,  
23 potentially varied, target audiences. End-users have a wide range of differing expertise and  
24 backgrounds, possibly influencing the decision-making process they undertake for a given  
25 forecast presentation. Our previous, linked study, examined how the presentation of  
26 uncertainty information influenced end-user decision making. Here, we shift the focus to  
27 examine the decisions and reactions of participants with differing expertise (Meteorology,  
28 Psychology and Graphic Communication students) when presented with varied hypothetical  
29 forecast representations (boxplot, fan plot or spaghetti plot with and without median lines),  
30 using the same eye-tracking methods and experiments. Participants made decisions about a  
31 fictional scenario involving the choices between ships of different sizes in the face of varying  
32 ice thickness forecasts. Eye-movements to the graph area and key, and how they changed  
33 over time (early, intermediate, and later viewing periods), were examined. More fixations  
34 (maintained gaze on one location) and time fixating was spent on the graph and key during  
35 early and intermediate periods of viewing, particularly for boxplots and fan plots. The  
36 inclusion of median lines led to less fixations being made to all graph types during early and  
37 intermediate viewing periods. No difference in eye movement behaviour was found due to  
38 expertise, however those with greater expertise were more accurate in their decisions,  
39 particularly during more difficult scenarios. Where scientific producers seek to draw users to  
40 the central estimate, an anchoring line can significantly reduce cognitive load leading both  
41 experts and non-experts to make more rational decisions. When asking users to consider  
42 extreme scenarios or uncertainty, different prior expertise can lead to significantly different  
43 cognitive load for processing information with an impact on ability to make appropriate  
44 decisions.

45

## 46 **1. Introduction**

47 The importance of understanding the most ideal approach for communicating uncertainty  
48 information, an established problem in geoscience communication, has been further  
49 highlighted by the current COVID-19 pandemic. As more detailed information is presented to  
50 and interpreted by more non-specialists, the decisions made as a result have a significant  
51 impact on health, society and the environment, so careful consideration of communication is  
52 essential. Within the environmental sciences, making forecasts of natural hazards useful to  
53 end-users depends critically on communicating in a concise and informative way. Particularly  
54 as end-users have a wide range of differing expertise, spanning a spectrum between geo-



55 physical scientists to those with no formal scientific training. Therefore, the way in which  
56 information is displayed is very important for avoiding misperceptions and ensuring  
57 appropriate steps are taken by end-users, especially when perceptions of natural hazards  
58 can differ between experts and non-experts (Fuchs et al., 2009; Goldberg & Helfman, 2010).

59 Part I of this study, which from here will be called “companion paper” (Mulder et al.,  
60 forthcoming), shows that, for all groups, great care is needed in designing graphical  
61 representations of uncertain forecasts. This is especially so when attention needs to be  
62 given to critical information, and the presentation of the data makes this more difficult. In  
63 particular, well known anchoring effects associated with mean or median lines can draw  
64 attention away from extreme values for particular presentation types (Broad et al., 2007;  
65 Nadav-Greenberg et al. 2008; Mulder et al., 2020). The availability of easy-to-use tools that  
66 make the development of complex graphical representations of forecasts quick and cheap to  
67 produce, poses new challenges for the geo-scientists. Here, we compare the response of  
68 three different groups of end-users with different levels of scientific expertise to the same  
69 series of forecast presentations to explore how more and less complex presentations  
70 influence decision making and perception.

71 Expertise differences may be due to greater familiarity with the ways in which hazard  
72 information is made available. This enables experts to make more economically rational  
73 decisions and to interpret uncertainty information more effectively (Mulder et al., 2020).  
74 However, the role of expertise remains unclear with some studies showing no differences in  
75 decision-making tasks with both experts and non-experts able to process and use forecast  
76 information to make decisions, with the inclusion of uncertainty information found to be  
77 useful for both experts and non-experts (Nadav-Greenberg et al., 2008; Kirschenbaum et al.,  
78 2014; Wu et al., 2014). Furthermore, it is unclear whether presentation of uncertainty  
79 information in visual formats results in benefits over using verbal and numerical expressions.  
80 For instance, uncertainty presented as graphical representations may help with  
81 understanding and interpretation (Susac et al., 2017). Additionally, research is required to  
82 examine differences in expertise, particularly as deterministic construal errors can be made  
83 as observers are often unaware that uncertainty is being depicted within visualisations  
84 (Joslyn & Savelli, 2021). Inappropriate information that captures attention is also often relied  
85 on, which can distort judgements (Fundel et al., 2019).

86 Experts are better at directing attention (through eye movements) to the important  
87 information required for making a decision. For example, in judgments of flight failures,  
88 expert pilots were found to make faster and more correct decisions, making more eye  
89 movements to the cues related to failures than non-experts (Schriver et al, 2008). Kang and



90 Landry (2014) also found non-experts to improve after they were trained with the eye  
91 movement scan paths of experts; training led non-experts to make fewer errors (false  
92 alarms) on aircraft conflict detection tasks. However, there is little research examining eye  
93 movements when experts and non-experts are required to make decisions using graphical  
94 and numerical forecast information. It is not clear which aspects of forecast information are  
95 being examined and when, and equally which, are being ignored.

96 More generally, research has shown that when viewing images, more fixations are made to  
97 informative regions and areas of interest (Unema et al., 2005). The times at which these  
98 fixations are made has been found to vary depending on task, decision type and expertise.  
99 Antes (1974) found that early fixations, in the first few seconds of viewing pictures, were  
100 towards informative areas. Goldberg and Helfman (2010) also showed that important regions  
101 of interest were fixated early during observation of different graphs. Experts have been  
102 shown to identify and fixate informative aspects of visual information more quickly and more  
103 often than non-experts (Maturi & Sheridan 2020; Charness, Reingold, Pomplun, &  
104 Stampe, 2001; Kundel, Nodine, Krupinski, & Mello-Thoms, 2008). As well as informative  
105 parts of a scene or image, Shimojo et al. (2003) reported that the likelihood that fixation  
106 would be made to the item preferred, increased over time, particularly in the final second  
107 before selection (see also Glaholt & Reingold, 2009; Simion & Shimojo, 2006; Williams et al.,  
108 2018). These results show that informative and preferred areas of images are selectively  
109 fixated early on, more often and for longer. As viewing evolves, fixations start to reflect final  
110 choices and preferences. The temporal development of this is task-dependent and  
111 influenced by expertise.

112 In our companion paper, we specifically examined how uncertainty information influenced  
113 interpretations and viewing behaviour. Regardless of expertise, participants were found to  
114 fixate towards median lines and less so to extreme values, with the type of graph and  
115 respective keys further influencing gaze and judgements. Here, we explore eye movement  
116 behaviour to similar hypothetical scenarios but with particular interest on differences due to  
117 participant expertise/background, following the research discussed, of gaze to graph areas  
118 and keys over different time periods of the decision-making process. As in our companion  
119 paper, we examine gaze patterns when faced with the task of making decisions about a  
120 fictional scenario involving the choices between ships of different sizes in the face of varying  
121 ice thickness forecasts (30%,50%,70%), when presented in different formats (boxplot, fan  
122 plot or spaghetti plot, with and without median lines).

123 We use eye-tracking techniques and exploration of the accuracy of decision tasks across  
124 expertise to address the following questions:



- 125 1. Does the presence of a median line and expertise affect gaze over the course of the  
126 decision-making process?  
127 2. Does expertise affect gaze to the key over the course of the decision-making  
128 process?  
129 3. Does expertise affect accuracy of decisions?

130

## 131 **2. Methodology**

### 132 **2.1 Participants**

133 Sixty-five participants took part in this study: twenty-two meteorology students, twenty-two  
134 psychology students and twenty-one graphic communication students recruited from the  
135 University of Reading (38 females, 27 males). Participants were aged 18–32 ( $M = 21.2$ ) and  
136 had completed 0–4 ( $M = 1.0$ ) years of their respective degrees. Meteorology students are  
137 considered to have more training in graph reading, scientific data use, and quantitative  
138 problem solving as part of their degree and in qualifying for the course, than students on  
139 other degree courses which have less of a focus in these areas. Within this study,  
140 meteorology students were therefore considered to have greater expertise compared to the  
141 psychology and graphic communication students, although psychology students are also  
142 likely to have statistical knowledge and experience reading graphs. The research team  
143 involved academics who taught on each of these subjects and therefore can substantiate  
144 these generalisations.

145

### 146 **2.2 Procedure**

147 Full methodological details are given in our companion paper, but to restate the core  
148 procedure: A hypothetical scenario of ice thickness forecast was provided to participants. In  
149 this paper we only examined the decision-task question where participants were asked to  
150 select which ship (small or large) to send across an icy strait 72 hours ahead of time using a  
151 72-hour forecast of ice thickness (see our companion paper for further details on the  
152 hypothetical scenarios). Ice thickness forecasts were presented in seven different types:  
153 deterministic line, box plot, fan plot and spaghetti plot. Each representation was presented  
154 with or without a median line. Each of these graph types was shown to represent 30%, 50%,  
155 and 70% probability of ice thickness exceeding 1 meter. While performing this task,  
156 participants wore an Eye link II eye-tracker headset which recorded eye movements of the  
157 right eye as they completed the survey. Head movements were restrained, and the eye  
158 tracker was calibrated to ensure accurate eye movement recording.



159 **2.3 Data analysis**

160 Two interest areas were formed from a post hoc classification to address our research  
161 questions (graph area and key). Three viewing periods across trials were created (early,  
162 intermediate, late). The exact definition of early, intermediate, and late differed by type of  
163 graph due to each style evoking slightly different viewing periods. Viewing periods for each  
164 specific graph type were of equal bins divided across the average time to complete the  
165 question and therefore ranged between 5 to 6 seconds. In this study, we report number of  
166 fixations and total fixation duration.

167 In our companion paper, our analysis of gaze was across all experimental trials and all  
168 tasks. However, as we are concerned about the viewing period and want to avoid effects of  
169 learning, we examine gaze when participants were faced with each graph type for the first  
170 time. Repeated exposure to graph type and the demand to make the same judgement may  
171 influence gaze patterns as informative parts of the figures are located more swiftly.

172 Therefore, six trials for each graph type for each participant were examined. We analysed  
173 the accuracy of responses to this question (making the safe and cost-effective choice of the  
174 two options) and gaze (number and total fixation duration).

175

176 **2.4 Ethics**

177 The University of Reading Ethics Board approved the study, and the study was conducted in  
178 accordance with the standards described in the 1964 Declaration of Helsinki. Participants  
179 provided written informed consent. The authors declare that there is no conflict of interest.

180

181 **3. Results**

182 Based on the results of our companion paper, we further explore the impact of the presence  
183 of a median line considering the viewing period, expertise and graph type. We then focus on  
184 fixation towards the keys including viewing period, expertise, graph type and the presence of  
185 a median line as variables. For both research questions a four-way mixed measures ANOVA  
186 was conducted including graph type, presence of a median line and viewing period as within-  
187 subject variables, and expertise as a between-subjects variable. Finally, we report the  
188 accuracy of responses for the ice ship decision task highlighting any differences due to  
189 expertise.

190



191 **3.1 Does the presence of a median line and expertise affect gaze over the course of**  
192 **the decision-making process?**

193 Our companion paper shows how the presence of a median line affects the location of  
194 participants fixations; eye movements were closer to the median line. Previous research by  
195 Mulder et al. (2020), further shows that the median line influences decisions independent of  
196 the type of graph observed. Here, we further examined how the median line influences eye  
197 movement behaviour when considering the viewing period from early to late stages, and  
198 different levels of expertise, as well as the graph type.

199 A main effect of presence of a median line was found for number of fixations and total  
200 fixation duration made to the graph area,  $F(1, 62)= 6.403$ ,  $MSE=32.747$ ,  $p=0.014$ ,  $\eta^2$   
201  $=0.094$ ;  $F(1, 62)= 7.125$ ,  $MSE=2386741.96$ ,  $p=0.01$ ,  $\eta^2=0.103$ . More fixations were made,  
202 and more time was spent fixating on the graph area of the display when no median line was  
203 present (fixation count  $M=8.74$ ; total duration  $M=2128.64$ ) compared to when a median line  
204 was provided (fixation count  $M=7.89$ ; total duration  $M=1887.47$ ).

205 A main effect of graph type was also found for number of fixations and total fixation duration  
206 made to the graph area,  $F(2, 124)= 15.098$ ,  $MSE=26.406$ ,  $p<0.001$ ,  $\eta^2=0.196$ ;  $F(2, 124)=$   
207  $16.810$ ,  $MSE=1635280.256$ ,  $p<0.001$ ,  $\eta^2=0.213$ . Boxplots elicited more fixations, and more  
208 time was spent fixating on boxplots (fixation count  $M=9.07$ ; total duration  $M=2222.21$ ) and  
209 fan plots (fixation count  $M=8.71$ ; total duration  $M=2091.04$ ) compared to spaghetti plots  
210 (fixation count  $M=7.17$ ; total duration  $M=1710.92$ ).

211 There was also a main effect of the viewing period for number of fixations and total fixation  
212 duration made to the graph area,  $F(2, 124)= 59.608$ ,  $MSE=36.762$ ,  $p<0.001$ ,  $\eta^2=0.488$ ;  $F(2,$   
213  $124)= 57.417$ ,  $MSE=2294640.505$ ,  $p<0.001$ ,  $\eta^2=0.481$ . There was found to be a greater  
214 number of fixations with longer dwell times on the graph area during early (fixation count  
215  $M=9.83$ ; total duration  $M=2399.96$ ) and intermediate (fixation count  $M=9.52$ ; total duration  
216  $M=2284.11$ ) viewing periods compared to later periods (fixation count  $M=5.60$ ; total duration  
217  $M=1340.09$ ).

218 There was no main effect of expertise on gaze behaviour measured by both fixation count  
219 and total duration;  $F(1, 62)= 0.536$ ,  $MSE=64.185$ ,  $p=0.588$ ,  $\eta^2=0.017$ ;  $F(1, 62)= 1.770$ ,  
220  $MSE=3970562.258$ ,  $p=0.179$ ,  $\eta^2=0.054$ , respectively.



221 As well as the main effects of median line, graph type and viewing period, there was an  
222 interaction between the median line and viewing period for total fixation duration,  $F(2, 124)=$   
223  $3.598$ ,  $MSE=1543871.74$ ,  $p=0.03$ ,  $\eta^2=0.055$ . Less time was spent fixating the graph area  
224 during the early and intermediate stages of viewing when a median line was present (Early  
225 total duration  $M= 2174.97$ ; Intermediate total duration  $M= 2137.79$ ) compared to when no  
226 median line was present (Early total duration  $M= 2624.96$ ; Intermediate total duration  $M=$   
227  $2430.43$ ),  $p<0.001$ ;  $p=0.05$ , respectively. However, no differences were found due to the  
228 presence (later total duration  $M= 1349.65$ ) or absence (later total duration  $M= 1330.54$ ) of a  
229 median line during the later stages,  $p=0.896$ . No other interactions were found to be  
230 significant. These findings support that the median line can reduce cognitive load; impacting  
231 the total fixation duration and number of fixations made on the graph area, particularly during  
232 early stages of the decision-making process, and adds to results from our companion paper  
233 that showed how fixation location was towards the median line when present, regardless of  
234 the type of graph.

235

### 236 **3.2 Is gaze to the key influenced by expertise and the viewing period during the** 237 **decision-making process?**

238 Mulder et al. (2020) found that particularly non-experts were misinterpreting data presented  
239 in a boxplot and suggest that not referring to the boxplot key led to making such errors. Our  
240 companion paper examined eye movements to the graph keys and found that less fixation  
241 was made to the spaghetti plot and boxplot keys compared to the fan plot keys. Here, we  
242 examine fixation to the key over different periods of the decision-making process. As non-  
243 experts can particularly misinterpret data from boxplots, we consider differing levels of  
244 expertise.

245 A main effect of graph type was found for number of fixations and total fixation duration  
246 made to the key,  $F(2, 124)= 42.900$ ,  $MSE=8.096$ ,  $p<0.001$ ,  $\eta^2=0.409$ ;  $F(2, 124)= 42.396$ ,  
247  $MSE=574225.040$ ,  $p<0.001$ ,  $\eta^2=0.406$ . More fixations were made, and more time was  
248 spent fixating on fan plot keys (fixation count  $M=2.45$ ; total duration  $M=626.79$ ) compared to  
249 both boxplot (fixation count  $M=1.48$ ; total duration  $M=387.75$ ) and spaghetti plot keys  
250 (fixation count  $M=0.56$ ; total duration  $M=127.13$ ), and more fixations and time spent on  
251 boxplot compared to spaghetti plot keys.





252 There was a main effect of the viewing period on the number of fixations that were made to  
253 the key within the display, as well as the total amount of fixation,  $F(2, 124) = 17.967$ ,  
254  $MSE = 6.593$ ,  $p < 0.001$ ,  $\eta^2 = 0.225$ ;  $F(2, 124) = 21.003$ ,  $MSE = 416719.669$ ,  $p < 0.001$ ,  $\eta^2$   
255  $= 0.253$ . More fixations and longer dwell time to the key occurred during the early (fixation  
256 count  $M = 1.61$ ; total duration  $M = 407.15$ ) and intermediate (fixation count  $M = 1.99$ ; total  
257 duration  $M = 515.33$ ) viewing periods compared to later periods (fixation count  $M = 0.90$ ; total  
258 duration  $M = 219.20$ ).

259 No main effect of the median line on gaze to the key, measured by both fixation count and  
260 total duration, was found;  $F(1, 62) = 0.175$ ,  $MSE = 7.574$ ,  $p = 0.677$ ,  $\eta^2 = 0.003$ ;  $F(1, 62) =$   
261  $0.061$ ,  $MSE = 543399.152$ ,  $p = 0.805$ ,  $\eta^2 = 0.001$ , respectively. Nor was there a main effect of  
262 expertise on fixation count and total fixation duration;  $F(1, 62) = 0.251$ ,  $MSE = 10.191$ ,  
263  $p = 0.779$ ,  $\eta^2 = 0.008$ ;  $F(1, 62) = 0.141$ ,  $MSE = 730099.249$ ,  $p = 0.869$ ,  $\eta^2 = 0.005$ , respectively.

264 An interaction between the graph type and viewing period for fixation count and total fixation  
265 duration was found,  $F(4, 248) = 3.578$ ,  $MSE = 4.724$ ,  $p = 0.007$ ,  $\eta^2 = 0.055$ ;  $F(4, 248) = 4.260$ ,  
266  $MSE = 330504.612$ ,  $p = 0.002$ ,  $\eta^2 = 0.064$ ., respectively. More fixations were made, and more  
267 time was spent fixating the boxplot key during the early (fixation count  $M = 1.68$ ; total  
268 duration  $M = 423.76$ ) and intermediate (fixation count  $M = 2.06$ ; total duration  $M = 577.11$ )  
269 stages of the viewing period compared to the later stage (fixation count  $M = 0.71$ ; total  
270 duration  $M = 162.39$   $p < 0.005$ . Similarly, more fixations were made, and more time was spent  
271 fixating the fan plot key during the early (fixation count  $M = 2.69$ ; total duration  $M = 695.64$ )  
272 and intermediate stages (fixation count  $M = 3.10$ ; total duration  $M = 791.37$ ) compared to the  
273 later stage (fixation count  $M = 1.55$ ; total duration  $M = 393.37$ )  $p < 0.005$ . However, no  
274 differences were found between viewing periods for spaghetti plots,  $p > 0.05$ . The reason for  
275 less fixation being to spaghetti plot keys generally, and no differences overtime, could be  
276 due to the intuitiveness of this form of plot and the simplicity of the key.

277

### 278 3.3 Does expertise affect accuracy of decisions?

279 Mulder et al. (2020) found no significant difference in accuracy of decisions made between  
280 the graph types, just in the amount of uncertainty interpreted from them. Here, accuracy  
281 responses on the number of times participants correctly identified which ship would be most  
282 economically rational to send were measured considering expertise and probability of risk.



283

	Meteorology	Psychology	Graphic Communication
30% probability	74%	66.2%	75.5%
50% probability	87%	70.1%	72.1%
70% probability	95.4%	96.1%	94.6%

284 Table 1. presents accuracy results for all probabilities of risk for differing expertise. A small ship is the  
285 correct ship to send for a 30% risk of ice thickness and a large ship for 50% and 70% risk levels.

286

287 Overall, participants were accurate in their choice of ship (Meteorology= 85.5%;  
288 Psychology= 77.9%; Graphic communication = 80.7%); however, some differences were  
289 apparent due to expertise. A one-way ANOVA shows differences in accuracy when  
290 presented with 50% probability of risk, which is the most challenging task,  $F(2,64)= 4.029$ ,  
291  $p=0.023$ . Multiple comparisons show meteorology students to be significantly more accurate  
292 than psychology students in choosing the large ship during these scenarios,  $p=0.035$ , and  
293 more accurate than graphic communication students, although this difference is not  
294 significant,  $p=0.08$ . No differences between expertise were found for the 30% and 70% trials,  
295  $p>0.05$ .

296

#### 297 4. Discussion and Conclusions

298 As scientific information is increasingly being presented to non-specialists graphically, it is  
299 important to consider how this information is delivered. This approach to open science, less  
300 dependent on expert interpretation, is a natural development as general scientific literacy  
301 increases and is welcomed by both scientific producers and consumers. As this approach  
302 develops, it becomes much more important to have a clear understanding of the biases in  
303 interpretation that results from different forms of data presentation. While relevant to many  
304 fields of science, there is a particular need for this understanding in the environmental  
305 sciences as environmental hazards increase and change.

306 Prior research presents mixed results, with some authors suggesting that when making  
307 slight variations to graph representations that display uncertainty, decisions and  
308 interpretations differ (Correll & Gleicher, 2014; Tak et al., 2015), whilst others show that  
309 despite greater discrepancies in forecast representation, such as between graphic  
310 visualisations and written forms, there are no differences (Nadav-Greenberg & Joslyn,  
311 2009). Furthermore, few studies explore how experts and non-experts interpret forecast



312 information from different types of graphical forecast representations (Mulder et al., 2020).  
313 The current research examines these areas further by using eye-movement techniques  
314 considering expertise, and the viewing period during the decision-making process when  
315 observing a range of graph types.

316 More economically rational responses to the ship decision were made by meteorology  
317 students (greater level of expertise) during the most difficult scenarios. We found  
318 participants, regardless of expertise, to spend less time fixating the overall graph when a  
319 median line was presented, particularly during early and intermediate stages of viewing. This  
320 provides more evidence for the anchoring bias suggested in previous papers (Mulder et al.,  
321 2020), and in our companion paper. Participants focussed on the key for boxplots and fan  
322 plots more during early and intermediate stages compared to later stages. This provides  
323 evidence that early stages of viewing are more exploratory and towards informative areas  
324 (Antes, 1974; Goldberg & Helfman, 2010). However, considering the results and the  
325 differences found due to graph type, spaghetti plots appear to be simpler to interpret,  
326 potentially reducing cognitive load, corroborating the findings in Mulder et al. (2020) that the  
327 spaghetti plot helped users interpret extreme values.

328 Overall, this study, together with the analysis in our companion paper, demonstrates that  
329 there are many challenges when presenting natural hazard data to both experts and non-  
330 experts, the way that information is portrayed can impact interpretations and decisions. It is  
331 important to note that the graph area and key discussed here are specific to the particular  
332 tasks presented in this study and are used as indicators of the impact of expertise, graph  
333 type and the viewing period. Furthermore, course of study within higher education was used  
334 as a proxy for expertise, with meteorology students being regarded to have higher levels.  
335 However, future research would benefit from examining behaviour and decisions of  
336 academics and forecasters who would be considered as experts.

337 Responses to which ship participants opt for due to the risk of ice thickness (small or large)  
338 supports the importance of expertise as accuracy reduces dependent on the probability of  
339 ice thickness, with those with greater expertise being more accurate during more uncertain  
340 situations. However, expertise appears to have little impact on eye movement behaviour  
341 within our study. The results show how median lines can reduce cognitive load drawing  
342 users to the central estimate regardless of expertise. However, it is important to note that a  
343 median line reduces the perceived uncertainty in a graphic, even when explicitly presented  
344 (Mulder et al. 2020), so use of a median line should be used when the amount of uncertainty  
345 in the estimate is less critical to understand. Use of the key within graphical representations  
346 can also impact interpretations of data. For forecast providers this suggests that standard



347 information design principles which seek to reduce visual noise in data presentation and  
348 draw the user to the critical parts can have major benefits for their ability to effectively  
349 communicate with both expert and non-expert end-users.

350 More broadly, taken together the two parts of the study suggest that incorporating eye-  
351 tracking and other techniques from cognitive science into the process of the design of  
352 forecast communication tools could be extremely fruitful. These techniques are now well-  
353 established with technology that makes them relatively cheap to set up and use. Graphical  
354 presentation of geo-scientific forecasts can happen with a range of breadth and longevity of  
355 communication in mind. While eye-tracking and related techniques would not be appropriate  
356 for all purposes, where graphics are being developed for routine and wide use, for example  
357 routine weather forecasts, this kind of approach would be a very valuable addition to end-  
358 user engagement. One obvious extension to the work in the two parts of this study is  
359 applying the same techniques to well-known and widely used geo-scientific forecast  
360 graphics.

361

## 362 **5. Author contributions**

363 Louis Williams: Conceptualization, Investigation, Formal analysis, Writing – original draft  
364 preparation

365 Kelsey Mulder: Writing – review & editing

366 Andrew Charlton-Perez: Funding acquisition, Writing – review & editing

367 Matthew Lickiss: Writing – review & editing

368 Alison Black: Funding acquisition, Writing – review & editing

369 Rachel McCloy: Funding acquisition, Writing – review & editing

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376 Reading Research Data Archive at <http://dx.doi.org/10.17864/1947.110>

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378 The authors declare that they have no conflict of interest.

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