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Visualization and Decision Making Design Under Uncertainty

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Visualization and Decision Making Design

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Under Uncertainty

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9 *Uncertainty is an important aspect to data understanding. Without awareness of*
10 *the variability, error, or reliability of a dataset, the ability to make decisions on that*
11 *data is limited. However, practices around uncertainty visualization remain domain-*
12 *specific, rooted in convention, and in many instances, absent entirely. Part of the*
13 *reason for this may be a lack of established guidelines for navigating difficult*
14 *choices of when uncertainty should be added, how to visualize uncertainty, and how*
15 *to evaluate its effectiveness. Unsurprisingly, the inclusion of uncertainty into*
16 *visualizations is a major challenge to visualization. As work concerned with*
17 *uncertainty visualization grows, it has become clear that simple visual additions of*
18 *uncertainty information to traditional visualization methods do not appropriately*
19 *convey the meaning of the uncertainty, pose many perceptual challenges, and, in*
20 *the worst case, can lead a viewer to a completely wrong understanding of the data.*
Q1 21 *These challenges are the driving motivator for this special issue.*

22 **V**isualization has become a core component of
23 any decision or risk analysis pipeline, and tools
24 for creating visualizations are quickly becoming
25 more and more accessible. In addition, the visual
26 literacy of the general public has been increasing due
27 to the pervasiveness of visualizations in everyday life.
28 As the appetite for decision making tools grows, so
29 does the need to convey error, confidence, missing, or
30 conflicting data visually.

31 However, practices around uncertainty visualization
32 remain domain-specific, rooted in convention,
33 and in many instances, absent entirely. Part of the reason
34 for this may be a lack of established guidelines
35 for navigating difficult choices of when uncertainty
36 should be added, how to visualize uncertainty, and
37 how to evaluate its effectiveness. Unsurprisingly, the
38 inclusion of uncertainty into visualizations has been
39 decried as a major challenge to visualization, and may
40 play a role in other current communication challenges,
41 like how to promote clear communication of

42 experimental effects despite incentives for research-
43 ers to overemphasize small effects, or how to explain
44 model workings and predictions in a way that is inter-
45 pretable. As work concerned with uncertainty visuali-
46 zation grows, it has become clear that simple visual
47 additions of uncertainty information to traditional
48 visualization methods do not appropriately convey the
49 meaning of the uncertainty, pose many perceptual
50 challenges, and, in the worst case, can lead a viewer
51 to a completely wrong understanding of the data.
52 Numerous studies point to challenges people have in
53 interpreting uncertainty—both conceptually and in
54 visual presentation. Visualizing uncertainty may be
55 perceived as conflicting with other goals of visualiza-
56 tion authors, like conveying credible information.
57 There is no single definition of uncertainty, since
58 the term umbrellas things like confidence levels, distri-
59 butions, and missing or erroneous data, among others,
60 and little by way of guidance to help visualization
61 authors understand how different sources of uncer-
62 tainty manifest in different scientific domains
63 and may warrant different visual approaches. Finally,
64 large and heterogeneous datasets pose challenges
65 based on their size and the need to assimilate data
66 from multiple sources, all with uncertainty of different
67 type and scale.

68	CHALLENGES TO UNCERTAINTY VISUALIZATION	
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70	Representation and Modeling Challenges	
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72	Types of Uncertainty	
73	Uncertainty comes in many forms, mathematical	change the perceived salience of uncertainty relative
74	measures and conceptual ideas. We group these	to text presentations?
75	potentially disparate ideas into the term uncertainty,	116
76	both for ease but also lack of understanding. Can we	117
77	develop a taxonomy of uncertainty types to help	
78	define categories of uncertainty types that may be	
79	treated in a similar fashion?	
80	Big Data Problems	
81	The large scale of the data we are seeing today is just	Understanding User Differences
82	going to grow. Many of the techniques to handle this	118
83	data use summarizations, sampling, or clustering, all	Risk interpretation changes from person to person, as
84	of which introduce uncertainties in and of themselves,	119
85	on top of the uncertainties within the data originally.	120
86	In addition, data fusion and assimilation pose a chal-	121
87	lenge for uncertainty understanding since sources,	122
88	types, and meanings of uncertainties may change	123
89	between combined datasets. How can we handle	124
90	these challenges? What kind of new algorithms need	125
91	to be developed and what are the most appropriate	
92	uncertainty quantification techniques and statistical	
93	methods?	
94	Propagation	
95	Uncertainty arises in all stages of the decision making	Perception
96	pipeline, from data gathering and generation, through	126
97	visual presentation. Is there a way to better under-	There are mechanisms within the human visual sys-
98	stand these uncertainties and provide guidelines to	127
99	how these different stages of uncertainty effect	128
100	understanding and decisions? Are there types of	129
101	uncertainty that are less impactful and thus need less	130
102	attention, or are there strong uncertainties in common	131
103	algorithms that may suggest better algorithms or at	132
104	the very least more attention by the community?	133
105	Comprehension Challenges	134
106	Challenges to Decision Making and Risk	
107	Analysis	
108	Though decision making under uncertainty and risk	Social Challenges
109	are well studied fields unto themselves, the unique	135
110	characteristics of decision making and analysis from	Ethical Risks and Incentives
111	visualizations raise questions that remain unanswered	136
112	in those bodies of literature. For example, visualiza-	Depending on the situation, conveying uncertainty
113	tions are often accompanied by text; should uncer-	137
114	tainty be visualized for users to properly integrate it	138
115	with text information? How does a visual channel	139
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		Collaboration
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		Decision making is often a collaborative process that
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164 the different parties involved (e.g., between uncer-
 165 tainty modelers and decision makers)? How can we
 166 design uncertainty visualizations that take into
 167 account the various sources of uncertainty in the data
 168 as well as at the cognitive and relational levels? What
 169 are the triggers and barriers for revealing and commu-
 170 nicating uncertainty in a collaborative context?

PAPERS IN THE SPECIAL ISSUE

171
 Q2172 Through the formal *IEEE Computer Graphics and*
 173 *Applications* review process of the 10 submissions, we
 174 accepted five papers for this special issue. In the arti-
 175 cle by Jin, Koesten, and Möller,^{A1} the authors present
 176 different interface designs of sliders to support deci-
 177 sion-making problems with three criteria. They present
 178 an exploration of the design space through an itera-
 179 tive development process with eight prototypes and
 180 the results of several evaluation studies with visualiza-
 181 tion experts and nonexperts. The article by Liu and
 182 Vuillemot^{A2} investigates a user interaction based on a
 183 function for users to generate fuzzy data attributes in
 184 a dynamic way to convey the uncertainty categoriza-
 185 tion and to better support visual data analysis. The
 186 article by Tominski et al.^{A3} explores how sets should
 187 be visualized. They develop a conceptual framework
 188 that brings together the information primarily relevant
 189 in sets (set membership, set attributes, and element
 190 attributes), as well as different plausible categories of
 191 (un)certainty and apply their framework to multiple
 192 visualization examples. The article by Gillmann et al.^{A4}
 193 notes that while visual analytics (VA) has become a
 194 standard tool to process and analyze data visually to
 195 generate novel insights, each component can intro-
 196 duce uncertainty in the visual analytics process. The
 197 authors propose a taxonomy of potential uncertainty
 198 events in the VA cycle. Finally, Matzen et al.^{A5} note
 199 that while visualizations are a useful tool for helping
 200 people to understand information, they can also have
 201 unintended effects on human cognition. This is espe-
 202 cially true for uncertain information, which is funda-
 203 mentally difficult for people to understand. The
 204 authors discuss the results of four experiments that
 205 compared visual and numerical representations of
 206 uncertainty and demonstrate that design choices are
 207 not neutral: seemingly minor differences in how infor-
 208 mation is represented can have substantial impacts
 209 on human risk perception and decision making.

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APPENDIX: RELATED ARTICLES

- 215
 A1. Y. Jin, L. Koesten, and T. Möller, "Exploring the design
 217 space of three criteria decision making," *IEEE Comput.*
 218 *Graph. Appl.*, vol. 43, no. 5, Sep./Oct. 2023. 219
 A2. L. Liu and R. Vuillemot, "A generic interactive
 221 membership function for categorization of quantities,"
 222 *IEEE Comput. Graph. Appl.*, vol. 43, no. 5, Sep./Oct. 2023. 223
 A3. C. Tominski et al., "Visualizing uncertainty in sets," *IEEE*
 225 *Comput. Graph. Appl.*, vol. 43, no. 5, Sep./Oct. 2023. 226
 A4. C. Gillmann, R. G. C. Maack, F. Raith, J. F. Pérez, and
 228 G. Scheuermann, "A taxonomy of uncertainty events in
 229 visual analytics," *IEEE Comput. Graph. Appl.*, vol. 43,
 230 no. 5, Sep./Oct. 2023. 231
 A5. L. E. Matzen, B. C. Howell, M. C. S. Trumbo, and
 233 K. M. Divis, "Numerical and visual representations of
 234 uncertainty lead to different patterns of decision
 235 making," *IEEE Comput. Graph. Appl.*, vol. 43, no. 5,
 236 Sep./Oct. 2023. 237

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