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Technical Section

Wiggle! Wiggle! Wiggle! Visualizing uncertainty in node attributes in straight-line node-link diagrams using animated wiggliness ☆

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ABSTRACT

Uncertainty is common to most types of data, from meteorology to the biomedical sciences. Here, we are interested in the visualization of uncertainty within the context of multivariate graphs, specifically the visualization of uncertainty attached to node attributes. Many visual channels offer themselves up for the visualization of node attributes and their uncertainty. One controversial and relatively under-explored channel, however, is animation, despite its conceptual advantages. In this paper, we investigate node "wiggliness", i.e. uncertainty-dependent pseudo-random motion of nodes, as a potential new visual channel with which to communicate node attribute uncertainty. To study wiggliness' effectiveness, we compare it against three other visual channels identified from a thorough review of uncertainty visualization literature—namely node enclosure, node fuzziness, and node color saturation. In a larger-scale, mixed method, *Prolific*-crowd-sourced, online user study of 160 participants, we quantitatively and qualitatively compare these four uncertainty encodings across eight low-level graph analysis tasks that probe participants' abilities to parse the presented networks both on an attribute and topological level. We ultimately conclude that all four uncertainty encodings appear comparably useful—as opposed to previous findings. Wiggliness may be a suitable and effective visual channel with which to communicate node attribute uncertainty, at least for the kinds of data and tasks considered in our study.

1. Introduction

Uncertainty is common to most types of data and can affect the visualization pipeline at any stage, from data acquisition, through data transformation, to rendering [1]. Effective visual communication of uncertainty in data is essential for a user's accurate interpretation and informed decision-making [2,3]. While common in some fields, such as meteorology [4], climatology [5], and biomedical sciences [6], the visualization of uncertainty remains underutilized across many other fields [7], such as network visualization. In this work, we focus on the field of network visualization, in which uncertainty is often discussed, but rarely visualized [8]. Uncertainty in network visualization can take many different forms, such as geometrical (embedding) uncertainty [9], topological (edge and node) uncertainty [10], edge attribute [11,12] uncertainty, or node attribute uncertainty [13]. We are particularly interested in the visualization of node attribute uncertainty, as it remains understudied despite node attributes being (the most) commonly included in many multivariate networks [14].

For the visualization of node attributes and their uncertainty, several visual channels present themselves, as outlined by Conroy et al. [8] and summarized in Fig. 1. The actual effectiveness of these visual channels' abilities to draw user attention to areas of uncertainty remains unexplored [8]. In this work, we highlight an often-overlooked uncertainty visualization method — animation — which remains uncommon even beyond network visualization [8]. We additionally compare it against other visual channels in terms of effectiveness.

We argue that animation holds significant potential for uncertainty visualization. While not universally applicable, common guidelines suggest emphasizing regions of high uncertainty [8,15]. Movement effectively draws attention without increasing cognitive load [16], and animation may help explain complex concepts like uncertainty while engaging users [17]. It also "frees up" other visual channels, which may already be in use for representing different data dimensions. While animation has been criticized in dynamic network contexts for being too complex for accurate interpretation [18], such concerns may be less

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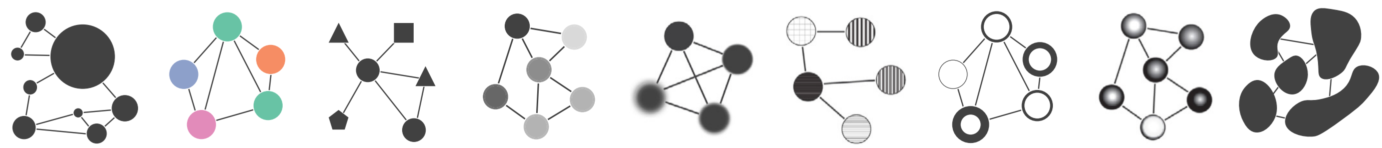

(a) Size (b) Hue (c) Shape (d) Saturation (e) Sharpness (f) Texture (g) Enclosure (h) Gradient (i) Splatting

Fig. 1. The nine identified visual channels with which to communicate node attributes, and uncertainty more specifically, according to Conroy et al. [8]: node size, node color hue, node shape, node color saturation, node sharpness or fuzziness, node texture, node enclosure, node gradient, and node splitting.

relevant for uncertainty visualization, where conveying relative rather than exact values is often sufficient [3].

We hypothesize that animation, while controversial, could be highly effective at visualizing uncertainty in node attributes and warrants further investigation. In contexts where uncertainty is critical, animation could be a valuable alternative to existing visual channels, as it could draw strong attention to regions of high uncertainty. However, whether animation can form an effective alternative to commonly employed visual encodings, both in terms of user preference and performance, remains largely unexplored. Similarly, the relative utility of standard uncertainty encodings in network visualization is still not well understood [8]. This work investigates the impact of different visual channels for uncertainty visualization on both user experience and performance.

In this paper, inspired by previous biomedical work [19–21], we present a novel approach to visualizing uncertainty in networks' node attributes using node "*wiggliness*" (W), i.e. animated pseudo-random motion. To compare this novel network uncertainty visualization approach to meaningful alternatives, we perform a thorough survey of uncertainty visualization literature. This corpus of literature is then categorized by application domain and uncertainty visualization approach to better understand the current landscape of the field (outside of the context of network visualization). From the identified approaches, we select three representative and effective uncertainty visualization techniques that can be applied to network visualization [8]: node saturation (S), node enclosure (E), and node fuzziness (F). To determine whether wiggliness holds value as an uncertainty visualization technique, we then conduct a large-scale, online, crowd-sourced user study in which we probe user performance and preference both quantitatively and qualitatively in a mixed-method setup.

In summary, we introduce animated node "wiggliness", a novel technique with which to represent attribute uncertainty in node-link visualizations, and compare it to enclosure, fuzziness, and saturation. A user study of 160 participants shows that all four methods offer comparable performance and perceived learnability, intuitiveness, and understandability.

2. Related work

2.1. Visualizing uncertainty in networks

While uncertainty visualization has received notable attention in fields such as biomedical or meteorological visualization, the same cannot be said of network visualization [8]. Here, we outline what has been done in regard to uncertainty visualization in networks.

Uncertain layouts. Unless nodes have some intrinsic 2D/3D positional information, a network's embedding is merely a function of the selected automatic layout algorithm. There is, thus, ambiguity in these layouts, depending on which layout algorithm is chosen or what hyperparameters are chosen for a specific layout algorithm. To address this ambiguity, Yan and Cui [9] opted to visualize the resulting embeddings side-by-side as an ensemble in order to allow users to investigate differences in the produced clustering of nodes. Similarly, Wang et al. [22] also visualize multiple such produced layouts, but they visualized them overlayed atop each other.

Uncertain edges. A graph's edges may have uncertainty attached to them and their weights. For an application-driven example hereof, Vehlow et al. [13], within the context of biochemical reaction network analysis, visualized the uncertainty in an edge using color saturation, i.e. the more certain an edge, the more saturated it is. Within the context of flow diagram visualization, Vosough et al. [23,24] investigated multiple different encodings of edge uncertainty, i.e. color saturation, edge gradient (fuzziness), and color hue. With the results of their conducted user study in hand, the authors ultimately conclude that color saturation works best for their purposes. More abstractly, some have also investigated different approaches to edge uncertainty visualization outside of any particular application domain. Here, Schwank et al. [11,12] investigated four possible edge encodings, namely edge dashes, waves, stripes, and blurring. They ultimately concluded that dashed edges communicated uncertainty most effectively. Finally, Guo et al. [25] investigated multiple pairs of visual encodings to communicate edge uncertainty.

Uncertain nodes and node attributes. Finally, a network's nodes and its nodes' attributes may also be uncertain. Cesario et al.'s [26] opted to encode the (un)certainty in a network's node attributes using the nodes' positions in 2D space. Returning to Vehlow et al.'s [13] biochemical reaction visualization, uncertainty in nodes' attribute uncertainty is visualized using color saturation; the more saturated, the more certain. Lastly, within the context of lattices, Collins et al. [3] visualized node uncertainty using transparency, border fuzziness, and position. Animation has, to the best of our knowledge, never been used to visually communicate node or edge attribute uncertainty.

2.2. Animation

Within the context of medical visualization, animation has been used for a variety of reasons, such as viewpoint selection, camera path planning, and focus+context visualizations [27]. Here, we aim to highlight the work done using animation for the purposes of uncertainty and network visualization.

Uncertainty visualization using animation. Examples of animation to visually communicate uncertainty (relevant to our own proposed approach) include (i) Blenkinsop et al.'s [28] random animations to communicate the results of fuzzy satellite classification data, (ii) Lundstrom et al.'s [19] probabilistic animation for medical volume visualization, (iii) Brown et al.'s [20] animated oscillation between two states to indicate uncertainty between them, (iv) Akiba et al.'s [29] animated transfer functions in medical volume visualization, (iv) Kale et al.'s [30] animated Hypothetical Outcome Plots, Ma et al.'s [31] dynamic visualization of uncertainty in medical features of interest, or Hermosilla et al.'s [32] visualization of uncertainty visualization of brain fibers.

Animation and network visualization. While an example of animation for uncertainty visualization in network visualization can be found [33], the majority of applications of animation center around dynamic, i.e. time-dependent, network visualization [34]. Very simply, such approaches map the time dimension of a network to time, i.e. animation frames [35]. Many examples of animated dynamic network visualization approaches exist, all of which aim to preserve a user's mental map between time steps while still highlighting changes between steps meaningfully, as seen in *GraphAEL* [36,37] or *Visione* [38] As a complete discussion of such animated dynamic graph visualization approaches is beyond the scope of this paper, we refer the interested reader to Beck et al.'s review of the topic [35]. While animation has found frequent use, empirical comparisons of animated with static/non-animated visualizations do not always paint a favorable picture of animation. For example, Robertson et al. [39] and Archambault et al. [40] both found (for certain tasks) small multiples to outperform animations in their evaluations. Similarly, Farrugia et al. [41] found static visualizations to generally outperform animation. However, these evaluations are seldom clear-cut. For example, Saraiya et al. [42] found animation to outperform interactive timeline visualizations, at least when the number of time points was few. Boyandin et al. [43] showed that animation led to more findings on adjacent time steps than small multiples. In general, the question of whether animation is beneficial to users in dynamic (and subsequently uncertain) network visualizations is, in our estimation, still far from settled.

3. Study

In this study, we aim to quantitatively and qualitatively evaluate the effect of node attributes' uncertainty representation on user performance and user experience. In order to ensure sufficient statistical power and qualitative feedback, we conduct a large-scale, between-subjects, online, crowd-sourced study. A between-subjects study design was chosen to ensure the study would take no longer than 30 min. Based on our prior experience with such online studies, this is the upper limit for online crowd-sourced studies, as longer studies negatively impact participant concentration, user performance, and the quality of qualitative comments received. Note that participants were required to complete the survey on a desktop or laptop computer with a display resolution of at least *1080p*.

First, we quantitatively evaluate the impact of four selected node attribute uncertainty representations on user performance. Specifically, we study the accuracy with which participants are able to answer a series of low-level graph analysis tasks and the time necessary to do so. Second, we also quantitatively evaluate the impact of these representations on user experience. Each participant is required to answer five questions regarding their experience on a 7-Point Likert scale at the end of the study, probing each participant's (i) perceived accuracy and efficiency, (ii) the ease with which participants used and learned the uncertainty representation, and (iii) the aesthetic appeal of the visualization. Finally, to go beyond a purely quantitative evaluation, we enrich said analysis with an additional qualitative analysis. To do so, after each completed task, participants were presented with optional feedback regarding the uncertainty visualization, as well as required feedback summarily at the end of the study.

In this section, we outline and motivate (i) the selection of uncertainty representations, (ii) the study's research questions, (iii) the data utilized for the study, (iv) the selection of low-level graph analysis tasks we investigate, and (v) the mixed-methods analysis of the produced data. The implementation, as well as our classification of the collected papers, has been made available on the Open Science Framework.[1]

3.1. Uncertainty visualizations

In this section, we describe how we selected and implemented our four uncertainty visualization channels, i.e. saturation (S), fuzziness (F), enclosure (E), and wiggliness (W).

3.1.1. Design rationale

Limited work has been done on uncertainty visualization in networks (Section 2.1). Thus, to select popular, representative, and effective visual channels for comparison, we first characterize the landscape of uncertainty visualization outside of the context of networks. To use as representative a sample of papers as possible, we collected all references from Jena et al. [44], who compiled a total of 286 papers from two previously published surveys [45,46] and through their own systematic search of the literature. We excluded papers that were not focused on visualization specifically (e.g. theoretical discussions of uncertainty), or not relevant to our survey of literature (e.g. review papers), resulting in a total of 191 papers. These papers were manually categorized by their application domain as well as their chosen visual encoding of uncertainty. We drew upon Jena et al.'s [44] already existing categorization of application domains, supplemented by our own categories where needed. For our categorization of chosen visual encodings, we drew upon work by Weiskopf [47], as it encapsulates many previously published taxonomies [1,2,15,48–51]. Here, Weiskopf categorizes visual approaches into three broad categories: **Hybrids and Systems**, **Display of Distribution**, **Summary Statistics**. Because Weiskopf's taxonomy is non-exhaustive, we added (where necessary) visual encodings from previous work, e.g. Padilla et al. [2], yielding a total of 31 unique approaches to uncertainty visualization. Fig. 2 shows the results of the categorization, as well as the total number of papers that featured each visual encoding. The categorization of these papers 2 has been made available through the Open Science Framework.

Some of these encodings have been argued to map more naturally and intuitively to uncertainty than others [2], such as fuzziness/fogginess [52,53], out-of-focus blur [54], transparency [55], location [50], color saturation [56], sketchiness [57], and noise textures [58]. Some of these visualization approaches (e.g. positional blur [59] or value-suppressing color-palettes [60]) obfuscate the value in question: the more uncertain it is, the harder to read it becomes. In our selection of visual encodings, we aim to use those that map the most naturally to uncertainty.

However, not all of the identified 31 approaches to uncertainty visualization (Fig. 2) are (straightforwardly) applicable to the visualization of node attribute uncertainty. We, therefore, applied our findings to the nine methods identified by Conroy et al. [8] (Fig. 1) and settled on three intuitive and popular visualization approaches to compare to animated wiggliness (W): (i) saturation (S), (ii) fuzziness (F), and (iii) enclosure (E). In summary, these three uncertainty encodings were selected as they are (i) applicable to node attribute uncertainty visualization [8], (ii) commonly utilized outside of the context of network visualization (Fig. 2), and (iii) deemed intuitive or effective in the context of uncertainty visualization [2]. Their selection ensures a fair and meaningful comparison, focusing on the most compelling alternatives currently available.

3.1.2. Selected approaches

In this section, we discuss the four selected approaches to uncertainty visualization that we use in this study. Additional (dis)advantages as discussed in the literature are further elaborated in Section 5.1.

Saturation. With 24 occurrences across 14 different application domains (Fig. 2), such as medical volume visualization [61] and spatial data analysis [62], saturation is one of the most commonly utilized **Summary Statistics** approaches to uncertainty visualization. Relatedly, brightness, sometimes called "*lightness*", is also frequently employed, with 28 occurrences across 10 application domains. Saturation is implemented through either a continuous [6,25,63] or ordinal [23,64,65] color scale, respectively indicating continuous or discretized levels of (un)certainty. Compared empirically to encodings within and outside of the context of uncertainty visualization, saturation (i) shows potential as an effective encoding [25,64,66,67], (ii) is liked by users [68], and (iii) deemed easily understandable [57]. We opt for a continuous saturation color scale, which denotes entities of low uncertainty with low saturation, and entities of high uncertainty with high saturation (Fig. 3(a)) [69,70].

[1] https://osf.io/e8927/?view_only=6295953d19ef439a8e9c11d5469f9310

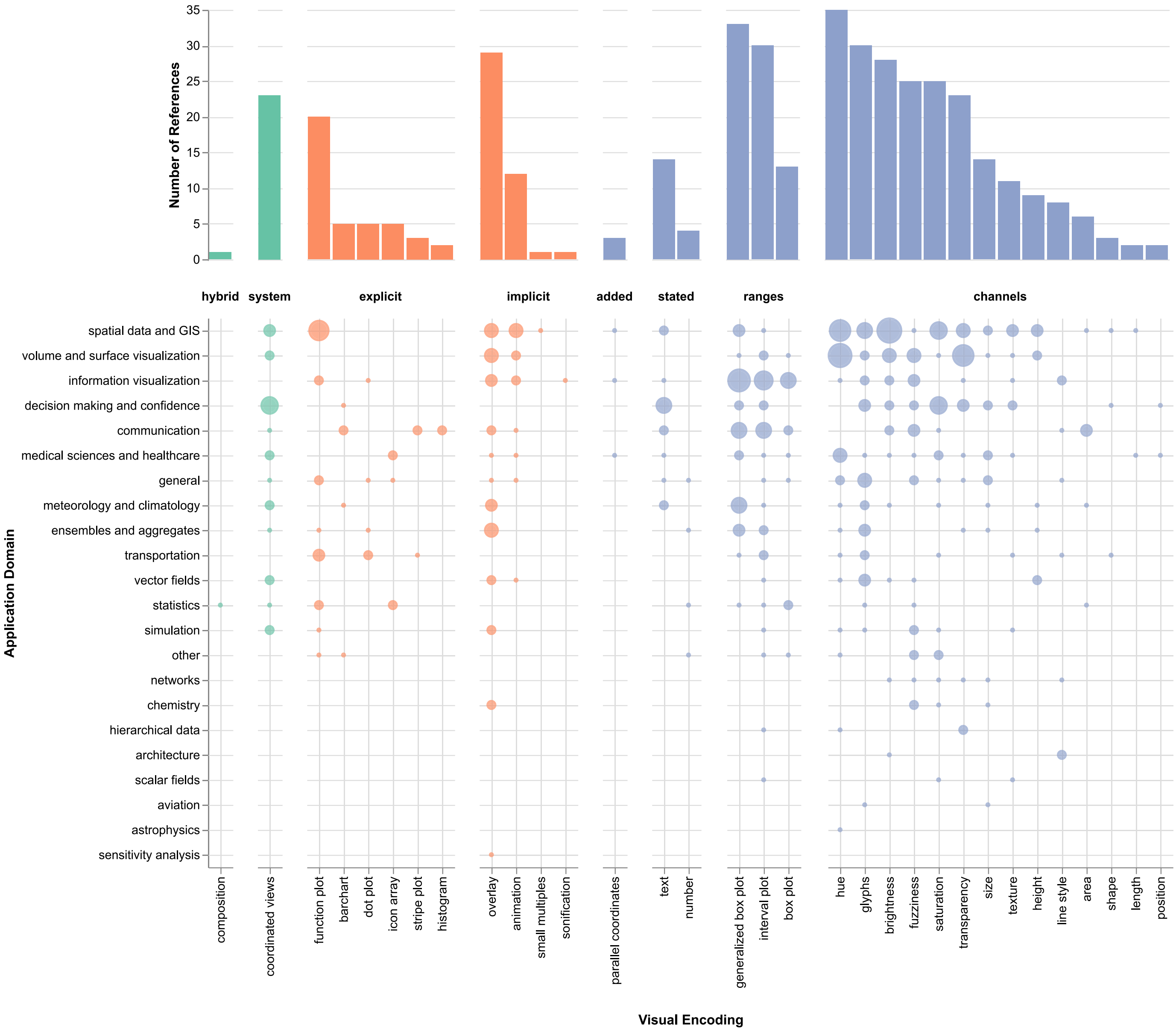

Fig. 2. Categorization of collected uncertainty visualization papers, visualized as a dot plot. The number of papers that mapped to a particular combination of application domain and visual encoding is visualized as a dot, whose surface area encodes the number of papers. Our classification of application domains were, where available, based on the work of Jena et al. [44]. Our classification of visual encodings is based on the taxonomy of Weiskopf [47]: all possible visual encodings fall within one of three categories, namely **Hybrids and Systems**, **Display of Distribution**, and **Summary Statistics**. Each of these categories is further broken down into subcategories, which in turn encapsulate individual visual encodings. Rows, i.e. application domains, are sorted in descending order of numbers of papers that mapped to said application domain. Within each subcategory facet, columns, i.e. visual encodings, are also sorted in descending order of numbers of papers that mapped to said visual encoding. The total number of papers that mapped to a particular visual encoding across application domains is visualized in the corresponding bar in the bar chart atop the dot plot. Papers could map to multiple application domains and visual encodings.

Fuzziness. With 25 papers across 13 different application domains (Fig. 2), such as volume rendering [71], flow diagrams [23] and lattice graphs [3], fuzziness is also a widespread **Summary Statistics** approach to uncertainty visualization. In empirical and qualitative comparisons of fuzziness against other visual encodings of uncertainty, fuzziness is generally recommended [64,65,72], described as intuitive and easily associated with uncertainty [57], and explicitly shown to be superior to other encodings in certain settings [73,74]. As described by Bonneau et al. [15], increased fuzziness intuitively communicates lower confidence, i.e. higher uncertainty. Here, we thus map increasing levels of uncertainty to increasing levels of fuzziness (Fig. 3(b)).

Enclosure. Node enclosure describes the style of the line border enclosing the surface of the (circular) node (Fig. 1(g)). Here, we define node enclosure as the *thickness* of this enclosing border. More specifically, akin to various types of *generalized box and interval plots* (Fig. 2), we map uncertainty to this thickness: the more uncertain a node's attribute, the thicker its border, in the same way that an interval or boxplot becomes wider/larger for less certain data. Such (generalized) interval and box plots (**Summary Statistics**) also form a very popular approach to uncertainty visualization outside of the context of networks (Fig. 3(c)), with 76 papers across 16 application domains mapping to the category as whole, and, more specifically, box plots, interval plots, and generalized box plots featured in 13, 33, and 30 papers, respectively. These types of range plots have found application/study across domains [75], such as information visualization [76], (non-expert) communications [77], and meteorology and climatology [78].

Wiggliness. Animation, with only 12 occurrences across 7 application domains (Fig. 2), remains one of the least popular **Display of Distribution** visual encodings for uncertainty visualization. As discussed previously (Section 2.2), animation has found some use, particularly in the visualization of time-dependent phenomena in medical [27] and spatial data [79] visualization. Even in the context of uncertainty visualization, animation has found some, if limited, use, both within the context of network visualization [80] and outside of it [30]. Here, inspired specifically by promising previous works on random [28], procedural [19], and looping [20] animation, we propose *wiggliness* as a new channel for uncertainty visualization in networks. Intuitively, wiggliness maps uncertainty to animated motion: the less certain the attribute of a node, the more that node moves randomly in (2D) space, drawing user attention to it (Fig. 3(d)).

Wiggliness visually conveys uncertainty by adding dynamic motion to uncertain nodes, conceptually making it easier for users to detect regions of high uncertainty at a glance. This approach leverages the human ability to notice movement, thereby minimizing cognitive effort while maximizing awareness of uncertainty. More specifically, each node $v \in V$ is initially located at some layout-algorithm-derived mid-point $p_v = (x_v, y_v)$. Per frame, this node is allowed to move randomly around said mid-point to some new position $p_v' = (x_v', y_v')$, as a function of its uncertainty-defined radius r; the greater the uncertainty, the greater the radius. This then requires the redrawing of both the node v as well as all edges connected to it, i.e. $\{\{v, w\} : \forall w \in V, w \neq v\} \cap E$. Prior testing showed that sampling x_v' and y_v' from uniform random distributions (independent of previous node locations) resulted in the clearest form of wiggliness. In contrast, position-dependent sampling (e.g., Gaussian noise or random walks) introduced apparent spatial patterns, which misleadingly suggested structure in the uncertainty. We also found that animating at 20 frames per second (fps) offered a smooth visual experience and consistent performance across systems. The combination of a uniform random node movement at 20 fps most effectively conveyed random, structureless uncertainty through visual jitter.

3.1.3. Implementation

All four uncertainty representations and network visualizations were implemented in *D3.js* [81]. More specifically, all graphs were laid out using *D3.js*' particle-based force-directed simulation algorithm, as it produced consistently visually appealing results very quickly. All four representations were implemented monochromatically. All four representations did not feature any interactivity, in order to ensure we were only studying the effects of the uncertainty visualization, instead of inadvertently their interactions with certain modes of user interactivity [19]. Moreover, interaction has been noted to increase the cognitive demand on users, especially non-expert ones [82,83]. Again, as we wish to avoid such cognitive load differences, or, more precisely, avoid their effect on our results, we implement static visualization in this study. Examples of the produced network visualizations, as they were presented to user study participants, can be found in Figure 3 of the supplement.

3.2. Research questions

Here, based on both previous research (see Section 2) as well as our own expectations, we formulate two research questions to be answered both quantitatively and qualitatively.

Q_1: Task-based turbulence. *Which low-level graph analytical tasks are best supported by which uncertainty visualization?* As pointed out by Conroy et al. [8], little work has been done to compare different uncertainty visualization strategies in networks. It is hence difficult to *a priori* hypothesize how the four selected uncertainty visualization strategies will fare in terms of user performance. Moreover, studies comparing animated solutions to uncertainty visualization to static approaches are also rare (Section 2.2). We thus ask ourselves which uncertainty visualization approach will prove most effective for certain low-level graph analysis tasks.

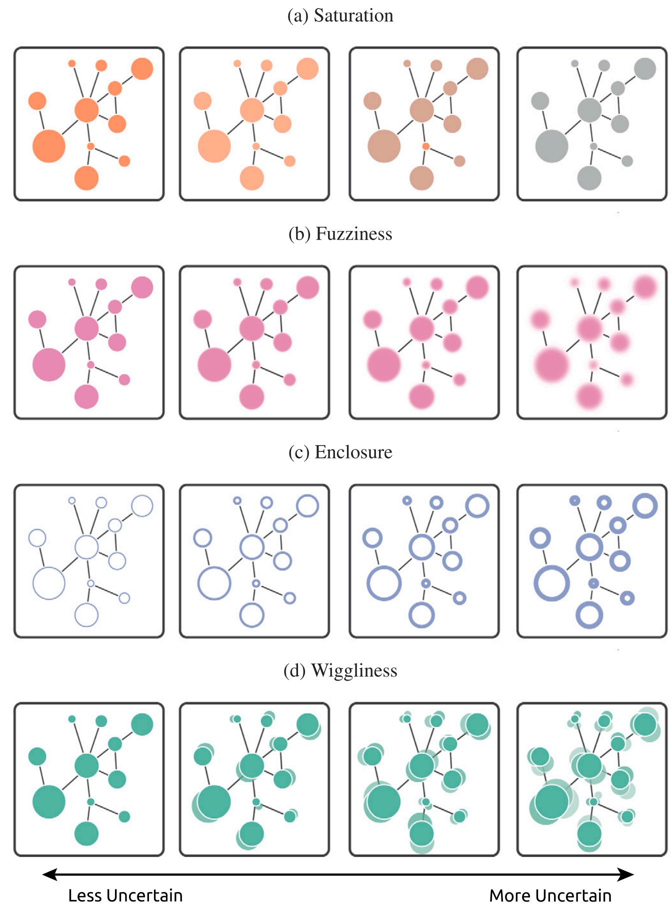

Fig. 3. Illustrative examples of (a) saturation, (b) fuzziness, (c) enclosure, and (d) wiggliness encoding uncertainty in a synthetic network of size $|V| = 9$ and $|E| = 11$. Note that, for illustration purposes, all nodes share the same degree of uncertainty for their attributes.

Q_2: Precarious preferences. *Which representation is preferred by users?* It has been argued that certain visual channels, such as fuzziness, transparency, or location, map more intuitively to uncertainty than others [2,15]. Here, while all four uncertainty visualization approaches were selected for their intuitiveness, we ask ourselves which representation will be preferred by users.

3.3. Data

In the following section, we briefly describe the graph data used in our study. Specifically, we discuss the process of generating graph topologies, node attributes, and node attribute uncertainties.

3.3.1. Topology

Similar to past comparative graph studies [84], we perform our user study using real graph topologies instead of simulated ones to avoid the non-representativeness often associated with simulated graphs [85]. As we aim to investigate eight topology and attribute-based tasks (see Section 3.5.1), a selected graph must have multiple realizations, i.e. one per task, to curb any learning effect across tasks. Additionally, to investigate the effect of the number of vertices on user performance and experience, we aim to investigate two sets of graphs: one small and one medium in size [86]. We select two sets of animal social networks of (roughly) two different sizes and densities, both collected from the *Network Repository* [87] that fulfill the selection criteria stated above.

First, we investigate a set of **raccoon proximity networks**. Each node represents a particular raccoon, and each undirected, weighted edge represents the number of times two raccoons were close to each other over the course of a day [88]. This dataset consists originally of 52 networks, each representing one day of a 52-day experiment. From these 52 graphs, eight were selected for their overall similarity (in terms of their number of edges and nodes), i.e. one per graph task. The number of vertices of the thus selected eight graphs ranges from $21 \leq |V| \leq 23$ and the number of edges from $50 \leq |E| \leq 82$, resulting in densities [89] ranging from $0.198 \leq d \leq 0.355$ (Fig. 4(a)).

Second, we investigate a set of **ant interaction networks**. Each node represents an ant of a particular colony, and each undirected, weighted edge is the number of mandible-to-mandible contacts between two ants over the course of a day [90]. This dataset consists of 8 graphs, each representing one day of an eight-day experiment. The number of vertices ranges from $24 \leq |V| \leq 31$ and the number of edges from $30 \leq |E| \leq 52$, resulting in densities [89] ranging from $0.073 \leq d \leq 0.137$ (Fig. 4(a)).

3.3.2. Node attributes

In our study setup, each node is to have one attribute attached to it: a single positive, continuous variable. Such a variable could, in a real dataset, represent a person's height in a social network or a gene's expression level in a gene-gene interaction network. In this study, however, this quantity is a purely abstract and theoretical one in order to avoid familiarizing users with a real dataset. Thus, for each node, we draw a single value, y, from a standard half-normal distribution (i.e. $y \sim |N(\mu, \sigma^2)|$, where mean $\mu = 0$ and standard deviation $\sigma^2 = 1$) (Fig. 4(b)). To visually communicate the node attribute's magnitude to the user, it is mapped to each node's surface area, i.e. the larger the node's attribute's magnitude, the larger its surface area.

3.3.3. Node attribute uncertainty

For each such drawn attribute magnitude, we must now simulate an uncertainty around its value. In a real-world dataset, such uncertainties could represent anything from measurement error to inherent variation in the data [48]. Here, it, again, is a purely abstract measure to avoid confusing users with a real dataset. Thus, for each node, we simulate a single positive value, s, between zero and one using a random uniform distribution, i.e. $s \sim U(a, b)$, where bound $a = 0$ and bound $b = 1$ (Fig. 4(c)). While a uniform distribution may not necessarily be representative of real-world uncertainties, it does ensure a sufficient amount of variation in uncertainty within each dataset to make each task sufficiently challenging and sufficiently different.

3.4. Training

To prepare participants for the study, we employ pre-study training. Following the terminology laid out by Nobre et al. [91], we make use of *Passive Training*, i.e. text-based tutorials. Specifically, in these tutorials, we (i) lay out how to read straight-line node-link diagrammatic network visualizations, and (ii) define node attributes and their uncertainty, as well as (iii) how these attributes and their uncertainties are visually represented to the user.

3.5. Study procedure

In this section, we outline the various aspects of user performance and experience that were measured.

3.5.1. User performance and tasks

Following the taxonomy of Lam et al. [92], we aim to evaluate user performance, i.e. study the speed and accuracy with which users are able to answer a series of low-level graph analysis tasks using a particular node attribute uncertainty visualization. Ultimately, we aim to quantitatively compare these speeds and accuracies between the four previously discussed uncertainty encodings (Section 3.1): the faster

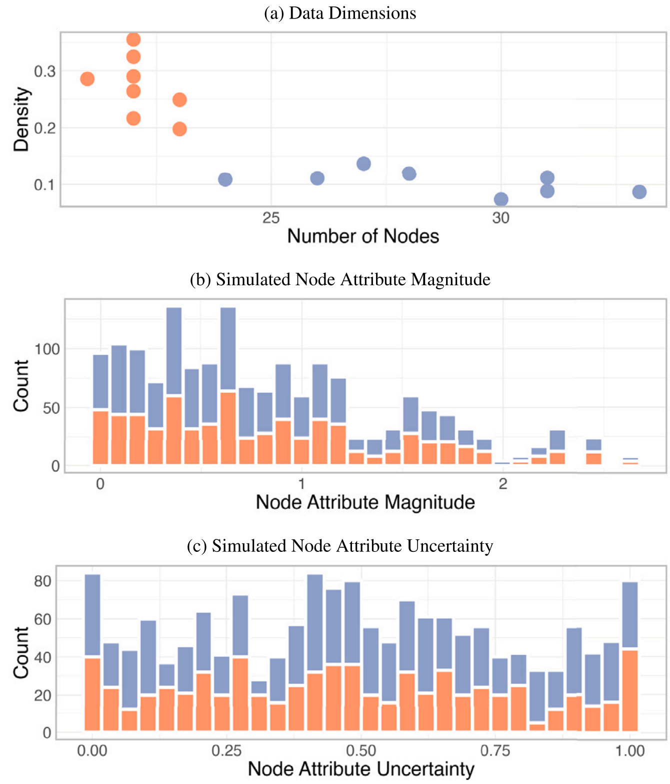

Fig. 4. Chosen/Simulated graph datasets' properties, specifically their (a) number of nodes and density, (b) half-normally simulated node attribute magnitude, and (c) uniform-randomly simulated node attribute uncertainty. Color-coded depending on the dataset, i.e. raccoons and ants.

and more accurately participants are able to answer tasks with a particular visual encoding, the more "readable" that particular encoding is [93,94] A key challenge lies in the selection of appropriate tasks for participants to complete. We investigate eight tasks in total, four attribute tasks relating to attribute magnitude and their uncertainty, and four tasks relating to the topology of the provided graphs.

First, we aim to investigate the user's ability to visually **identify and locate nodes of extreme uncertainty and attribute magnitude**. Following the taxonomy of Lee et al. [95], we investigate four "*Attribute Tasks*" "*On the Nodes*". Following the taxonomy of Amar et al. [96], we are particularly interested in tasking users with "*Finding Extrema*" in the data. Specifically, we aim to investigate four key tasks, namely

A_{max} Locate the node with the largest attribute magnitude.
A_{min} Locate the node with the smallest attribute magnitude.
U_{max} Locate the node whose attribute is the most uncertain.
U_{min} Locate the node whose attribute is the least uncertain.

As we anticipate nodes of greater attribute magnitude to be more readable than those of smaller magnitude, owing to their greater surface area, we deliberately control the assignment of attribute magnitude to attribute uncertainty. Additionally, we also anticipate the identification of particular nodes with higher attribute uncertainties to be more difficult, as these will be blurrier or wigglier. To control for these anticipated differences, a participant (for a particular uncertainty visualization approach) is assigned to either a "large" or "small" study run. In a "large" study run, the answers to A_{max} and A_{min} are those nodes with the *largest* attribute uncertainty. Similarly, for U_{max} and U_{min}, the answers are those nodes with the *largest* attribute magnitude. Conversely, in a "small" run, the answers to A_{max}/A_{min} and U_{max}/U_{min} are the nodes with the *smallest* attribute uncertainty and node attributes, respectively. In this way, all possible combinations of small and large attribute magnitudes and attribute uncertainties are controlled for and investigated.

Beyond communicating attribute uncertainty, an effective uncertainty encoding should not interfere with a user's ability to make sense of a graph's topology. Hence, second, we investigate the user's ability to **visually parse the topology of the presented graph** for a given uncertainty visualization encoding. Specifically, following the topology of Lee et al. [95], we investigate two "*Overview*" and two "*Topology*" tasks:

$\mathbf{O_{nodes}}$ Estimate the number of nodes in the graph.

$\mathbf{O_{edges}}$ Estimate the number of edges in the graph.

$\mathbf{T_{max}}$ Identify the node with the most neighbors in the graph.

$\mathbf{T_{min}}$ Identify the node with the fewest neighbors in the graph.

The answers to the previously discussed "*Attribute-based* Tasks" should have no bearing on users' abilities to make sense of the graph's topology. Thus, for each task O_{nodes}, O_{edges}, T_{max}, and T_{min}, users are randomly assigned on of the previously discussed "*large*" or "*small*" study runs. For the exact phrasing of these questions, i.e. as they were presented to users, please refer to Table 4 in the supplement.

3.5.2. User experience

Following Lam et al.'s [92] seven scenarios, we also aim to investigate user experience, i.e. perceived effectiveness and preferences. Thus, at the end of the study, users are presented with five statements to be answered on a 7-point Likert Scale:

$\mathbf{S_{learn}}$ The uncertainty visualization was easy to learn.

$\mathbf{S_{use}}$ The uncertainty visualization was easy to use.

$\mathbf{S_{pleas.}}$ The uncertainty visualization was aesthetically pleasing.

$\mathbf{S_{quick}}$ The uncertainty visualization allowed me to answer questions quickly.

$\mathbf{S_{acc.}}$ The uncertainty visualization allowed me to answer questions accurately.

Participants were presented with exactly these statements.

3.5.3. Qualitative feedback

Finally, we investigate user performance and experience qualitatively to understand *why* we observe certain quantitative trends. After each task (Section 3.5.1), users were able to optionally explain how the assigned uncertainty visualization either assisted or hindered them in answering the task. At the end of the study, users provide two points of feedback, either in favor or against the uncertainty visualization, explaining how it either assisted or hindered them.

3.6. Analysis

3.6.1. Quantitative evaluation

For each task, we record the participant's answer as well as the time taken to submit said answer. Based on the thus collected answers, the accuracy can be calculated for each task. For example, for task A_{max}, the accuracy is defined as the submitted answer's attribute magnitude divided by the actual (ground truth's) attribute magnitude. Alternatively, for task T_{min}, the accuracy is defined as the ground truth node's degree divided by the submitted node's degree.

Here, as assumptions of normality could neither be made nor (as will be discussed in Section 4) validated when probed with Shapiro–Wilk tests, we cannot make use of a conventional *ANOVA* for our statistical analysis. Instead, we turn to Wobbrock et al.'s *non-parametric aligned rank-transformed ANOVA* for our analysis [97]. The overall statistical impact of the uncertainty visualization approach on the time taken per task, task accuracy, and user experience is then assessed using an omnibus F-test. If significant, said F-test is followed by a series of pairwise comparisons of all uncertainty visualizations' estimated marginal means [98]. All tests were performed with a standard *a priori* Bonferroni-adjusted family-wise type-I error rate of $\alpha = 0.05$.

3.6.2. Qualitative evaluation

For each participant, we collect up to nine pieces of qualitative feedback, i.e. comments. These collected comments are then broken up into individual utterances. Note that some comments may also consist of only a single utterance. These utterances are then analyzed initially individually and then jointly by three coders in iterative coding sessions [99]. During the first individual coding session, each coder assigns a single code to each utterance as well as a positive or negative qualifier. These individual utterances and qualifiers are iteratively unified across coders until all coders reach 100% consensus.

4. Results

Here, we describe the quantitative and qualitative results obtained from the previously described user study.

4.1. Participants

In order to study the quantitative and qualitative effects of uncertainty encoding on user performance and experience, we conducted a large-scale, online user study. More specifically, we recruited 160 paid participants using the Prolific platform: [100] 20 per representation and dataset, i.e. 40 per uncertainty encoding total. Each participant was paid 11£ per hour for about 15 − −20 min of work. Of the 160 recruited participants, 83 self-identified as "male", 77 as "female". The average participant's age was 33. The youngest recruit was 18 years old, and the eldest was 72 years old. In terms of highest completed academic degree, 38 had completed high school, 76 had obtained a Bachelor's degree, 44 had finished a Master's program, and 3 had completed a PhD. Finally, 29 participants report "No Experience" with networks or graphs, 44 "Little Experience", 43 "Some Experience", 37 "Good Experience", and 8 "Extensive Experience". When probed statistically, no significant association between experience level and task accuracy or time could be established.

4.2. User performance

For each of the eight investigated tasks (Section 3.5.1), each participant's time as well as task accuracy were recorded, as visualized in Figures Suppl. 1 and 5, respectively. When statistically probed (Section 3.6.1), no statistically significant effects of uncertainty representation on either time or task accuracy could be detected. We direct the reader to Tables 1 and 2 in the supplement for a detailed account of the statistical results.

4.3. User experience

As discussed previously (Section 3.5.2), participants were required to answer five questions regarding their experience on a 7-point Likert scale. When probed statistically (Section 3.6.1), no statistically significant effect of uncertainty representation on user experience could be detected. Again, the reader is directed to the supplement, specifically Table 3 and Figure 2, for more details.

4.4. User feedback

As described previously (Section 3.5.3), we collected qualitative user feedback per task (optional) and summarily at the end of the study (mandatory). In total, 726 comments were collected from the 160 participants throughout the study. These comments were then broken down further into 893 utterances. During the first round of inductive coding, the three coders individually came up with 35, 99, and 27 different codes for the identified 893 utterances. These codes were discussed and unified until coders agreed upon 15 unique codes, grouped in 4 broader categories, namely *layout*, *effort*, *engagement*, and *usability*. During said discussion, utterances of no or little value were also removed (majority

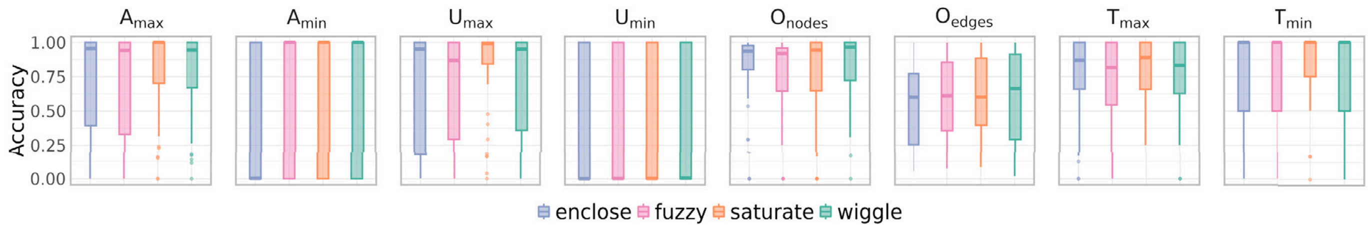

Fig. 5. Participants' task accuracies visualized per task and per uncertainty encoding, represented as a box-and-whisker plot. The box's center represents the values' median and its hinges the first and third quartiles. The whiskers represent 1.5 times the interquartile range.

vote), leaving a total of 512 utterances. In the final deductive coding step, each coder assigned one of the 15 agreed-upon codes to each of the remaining 512 utterances. Moreover, each utterance was also labeled as either positive or negative (−*negative*, +*positive*). During a final meeting, the three coders discussed each of their deductively coded utterances, until for each of the remaining utterances consensus was achieved. The results of this coding are presented in Fig. 6.

Layout. Layout (38 utterances) describes how negatively or positively the topological properties were perceived by users. This consists of the *node placement* (−11, +1) and *edge placement* (−25, +1). Examples hereof included comments such as "*[The visualization] hindered me just because there were a lot [of nodes]*" or "*[Edges] all look the same and sometimes almost overlap, I wasn't able to accurately count them*".

Effort. Effort (69 utterances) describes how much effort a participant had to invest to answer questions using the presented uncertainty encoding. This includes the *cognitive load* (−47, +11), the *temporal effort* (−2, +5) required, and the *physical effort* (−4, +0) needed, e.g. "*[...] Negative: one has to give a maximum concentration to avoid mistakes.*", "*[...] it [took] time to find the correct answer*", and, "*[...] Negative: Some parts were straining on the eyes.*" respectively.

Engagement. Engagement, the smallest category with only 35 utterances, describes utterances relating to active participation, commitment, or involvement. This comprises how *intellectually engaging* (−0, +13) and *affectively engaging* (−0, +9) it was, as well as how *aesthetically pleasing* (−1, +12) the uncertainty encoding was. Examples include, respectively, "*It was a very stimulating study [...]*", "*I really enjoyed this! [...]*", and "*I found the uncertainty visualization aesthetically pleasing [...]*".

Usability. Finally, usability, the largest category with 214 utterances total, contains utterances related to how usable a particular uncertainty encoding is. This includes how *confident* (−26, +2) users were in their given answers, e.g. "*[the visualization] enabled me to provide accurate answers [...]*". It also included how easy or difficult users found *comparing* (−35, +8) different attribute levels or certainty, e.g. "*it was difficult to compare the [enclosure's] thicknesses*. Additionally, usability included how *intuitive* (−4, +8) the uncertainty encoding was, e.g. "*[...] Having never seen this before it was easy to pick up*". Moreover, it included how *understandable* (−18, +9) the encoding was, e.g. "*[The visualization led to] confusion or misinterpretation.*". Penultimately, it included how *readable* (−23, +45) the encoding was, e.g. "*The uncertainty visualization effectively communicated the uncertainty levels, making it easy to identify nodes with high or low certainty.*". Finally, it also included how easy or difficult it was to gain an *overview* (−2, +16) of the data, e.g. "*[...] it was easy to access the information with a quick look.*".

5. Discussion

In this section, we discuss the results, both quantitative and qualitative, of our crowd-sourced user study.

5.1. Quantitative results

Surprisingly, the four investigated uncertainty encodings (Section 3.1) fared equivalently in terms of their produced user performance (Section 4.2). No statistically significant effects of uncertainty encoding on either time taken or task accuracy, and subsequently no statistically notable pairwise differences, could be detected. These findings are corroborated by a visual inspection of the results (Figs. 5 and Suppl. 1). Past investigations and evaluations have been rather critical of animation as a visual channel, especially within the context of uncertainty visualization. One possible explanation is that noted limitations, not only of animation, but also of saturation and fuzziness, ultimately balance each other out. Here, we briefly link our observed results to the disadvantages of these techniques documented in literature.

Limitations of fuzziness. First, fuzziness makes precise quantification difficult both from a mapping and cognitive perspective, i.e. the exact level of uncertainty may not be clear [55,101]. This is corroborated by utterances left by participants regarding the comparability of levels of uncertainty, e.g. "*There is not enough contrast to be accurate [when comparing relative levels of uncertainty.*" or "*[...] nodes can confuse you [as they look] same*". Second, fuzziness does not always work well in conjunction with other visual variables, e.g. shape or transparency: while intuitively communicating the presence of uncertainty, fuzziness may interfere with other visual channels and obfuscate their meaning and mapping [75]. Indeed, one participant explicitly mentioned that "*It's hard to tell apart same uncertain level of attribute when [attribute] values are very much different*", highlighting the negative interaction between the uncertainty's fuzziness and the attribute level's node size. Finally, small differences may be hard to visualize and detect by users of the visualization [55]. In line herewith, it would indeed appear as though detecting the least uncertain, i.e. the least fuzzy, node (U_{min}) proved difficult for participants (Fig. 5), though this particular task proved difficult across all four uncertainty encodings.

Limitations of saturation. First, human perception of brightness/saturation is not linear, i.e. small changes are not perceived equally along the spectrum, which can lead to misinterpretation of uncertainty [102]. Moreover, the number of meaningfully distinguishable levels of brightness/saturation is relatively small and thus not advisable for larger ranges [102]. Looking at the quantitative results of our study (Fig. 5), it is noticeable how, for all four visual encodings, participants struggled to identify the least uncertain node (U_{min}). For saturation specifically, this could be explained by this aforementioned non-linear perception as well as the poor distinguishability of different levels. Indeed, it is striking how many utterances were left lamenting the poor comparability of different saturation levels, e.g. "*Minor differences in [saturation are] not [...] visible to the naked eye*" or "*[...] it was hard to identify the saturation of some shades when it came to the nodes with least certainty [...]*". Third, brightness/saturation may also be easily confused with other variables, such as intensity, and may also interfere with chosen (background) colors [102], though we noted no results, either quantitative or qualitative, in this regard. Fourth, brightness/saturation, when combined with other visual channels, may

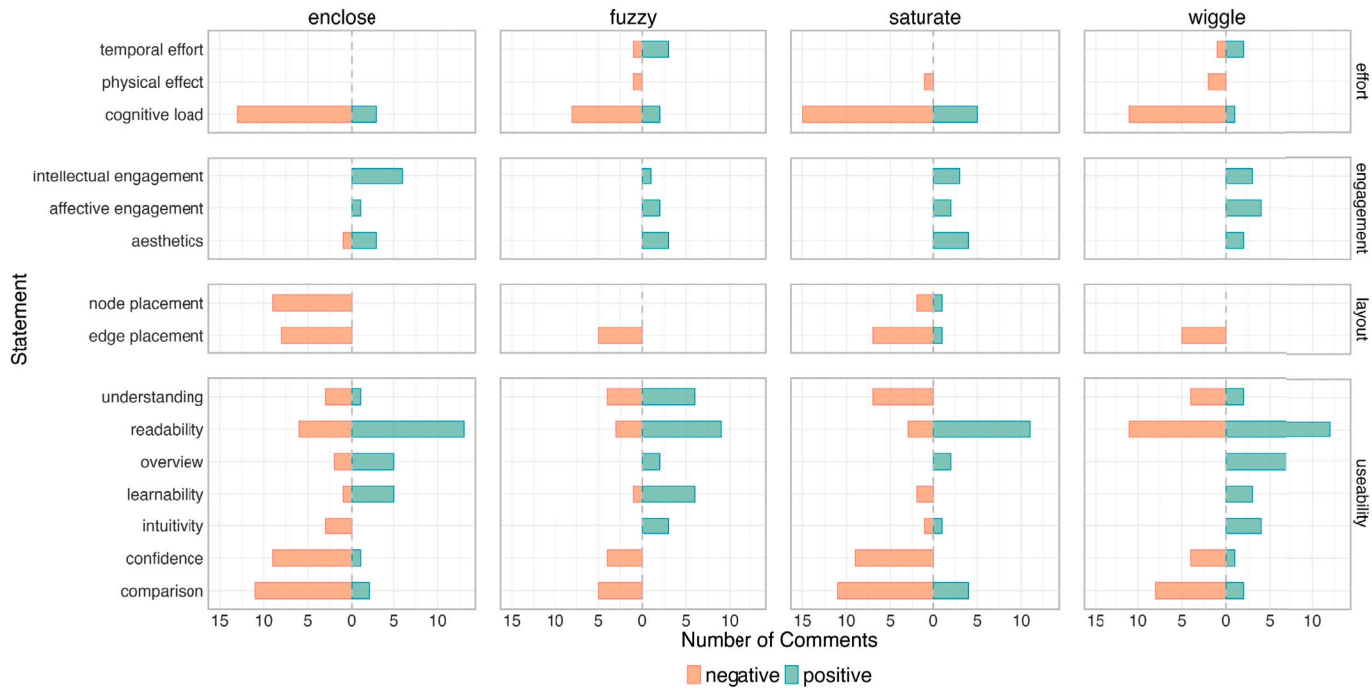

Fig. 6. The number of negative and positive statements made by participants relating to (i) effort, (ii) engagement, (iii) layout, and (iv) usability (rows) for each of the four representations (columns). Comment counts by statement type are color-coded based on whether they are negative or positive.

be overwhelming to the user, i.e. it does not necessarily match well with other encodings [102]. Again, looking at the aforementioned numbers of utterances left regarding comparability, it is interesting that a number of them complained specifically about this effect, e.g. "*[...] bigger nodes may appear more saturated than smaller nodes of the same saturation.*" or "*The more saturated, the larger the appearance.*".

Limitations of animation. First, animation has been argued to increase the cognitive load a user experiences, especially when multiple moving elements are present, i.e. as is the case with wiggliness [19]. With multiple nodes all wiggling simultaneously, a user could have had trouble comparing uncertainty levels across/between them. Looking at the qualitatively coded utterances left by participants (Fig. 6), wiggliness proved to not be any more cognitively challenging than any of the other uncertainty encodings, though some participants did explicitly mention the added effort required, e.g. "*[...] Excessive wiggliness can become visually distracting or overwhelming, especially in dense or complex networks [...]*". Second, similar to fuzziness, the mapping of uncertainty to wiggliness may make quantifying exact levels of uncertainty difficult [19]. Here, in line herewith, it is interesting to note that a number of participants did indeed leave comments such as "*There wasn't much of a difference in wiggliness between a few nodes, so it was hard to determine which was moving the most*". Third, animation is fundamentally limited by its temporal resolution with regard to a user's cognitive limits. If the speed of the animation does not match a user's viewing speed or attention, the user may miss critical details [18,103]. However, we could not identify any particular qualitatively coded utterances that would support a claim for additional temporal demand. Fourth, motion, and animation more generally, are strongly associated with changes over time. This may cause some confusion in users with such preconceived associations [18,103], though we did not observe any comments corroborating this claim. Finally, animation has been found to induce visual fatigue over time, which may negatively impact the accuracy and speed with which users are able to navigate and parse the visualization [19]. While one participant did explicitly describe the experience of working with wiggliness as "*[...] straining on the eyes.*", we were unable to identify any additional cognitive demand, physical effect, or cognitive load.

5.2. Qualitative commentary

Here, we enumerate several interesting observations regarding the qualitative feedback received from users. Where possible, we use these qualitative results to inform or explain our observed quantitative results.

Learnability and intuitivity. A key question underlying any (novel) uncertainty encoding is how easily it is to comprehend and whether it is truthful to the data it should actually represent. Here, we look at users' responses regarding an encoding's *learnability* and *intuitivity*. Interestingly, wiggliness was viewed exclusively positively in terms of its learnability (W: +3) and intuitivity (W: +4), described by two participants as "*[...] easy to figure out*" or "*[...] easy [to] interpret*". Comments left regarding enclosure, fuzziness, and enclosure, on the other hand, were not always positive regarding their learnability (E: [−1, +5], S: −2, F: [−1, +6]) and intuivity (E: −3, S: [−1, +1], F: +3). Given these small differences, however, we argue that the four uncertainty representations are ultimately comparable in terms of both their learnability and intuitivity. Unless the target user group is strongly familiar with a particular representation of uncertainty, we argue that animated wiggliness could form an equally learnable/intuitive representation as conventional alternatives, at least for the kinds of data and tasks presented here, i.e. relatively simple, low-level tasks [95] applied to small to intermediate-sized graphs [86]. It remains to be seen whether wiggliness (and animation more generally) is a suitable representation of uncertainty for more complex datasets and tasks.

Understanding and readability. Related to intuitivity and learnability, *understanding* and *readability* describe how well participants were able to utilize the presented uncertainty encoding. Regarding understanding, the four representations are fairly comparable (E: [−3, +1], F: [−4, +6], S: −7, W: [−4, +2]). However, when looking at readability, we note that those using wiggliness were slightly more critical (W: [−11, +12]) than those using the other three encodings (E: [−6, +13], F: [−3, +9], S: [−3, +11]). Comments left regarding wiggliness' poorer readability included "*certain movements/wobbles can create an optical illusion almost [...]*" or "*[...] the visualization did not clearly show the* *uncertainty or variability in the data [...]*" However, for the smaller to medium-sized graphs presented here, this difference in perceived readability had no impact on users' quantitative results (Fig. 5). However, it is worth asking whether, with larger and denser graphs, wiggliness could lead to a statistically notable decrease in either user performance or experience. We argue that this is broadly in line with the work of Lundström et al. [19] who concluded that "*animation methods [were an] effective approach for uncertainty visualization*". We thus argue that experimental follow-up work is needed to study the impact of wiggliness on user understanding and performance for more complex datasets and tasks.

Overview. *Overview* describes how easily a participant was able to quickly navigate the visualization in order to identify core aspects of the data. Here, we note that wiggliness (W: +7) was noted exclusively positively and more often than the other uncertainty encodings investigated (E: [−2, +5], F: +2, S: +2). Comments left by users of wiggliness noted the ease with which they were able to quickly identify regions of high and low uncertainty, e.g. "*[...] at a quick glance large differences in uncertainty can be easy and obvious to spot due to differences in wiggling [...]*" or "*[...] The movement draws attention to uncertain nodes, helping prioritize focus during analysis.*". Such utterances are in line with the speculation of Ehlschlager et al. [79], who posited that audiences may find animation useful for "quick qualitative impressions of the magnitude of uncertainty". As noted previously, (smaller) differences were more difficult to detect using wiggliness. This could point towards wiggliness being useful for big-picture, qualitative impressions of uncertainty instead of fine-grained comparisons of smaller differences, i.e. allowing users to quickly identify (groups of) nodes with high or low uncertainty.

Confidence and comparability. *Confidence* and *Comparability* describe the degree to which study participants were sure of their answers, particularly when comparing nodes' attribute levels and attribute uncertainties. In general, users expressed low confidence in their given answers across uncertainty encodings (E: [−9, +1], F: −4, S: −9, W: [−4, +1]). Across representations, participants also expressed difficulty in comparing attribute levels and uncertainties (E: [−11, +2], F: −5, S: [−11, +4], W: [−8, +2]). This low confidence and difficulties in comparing node attribute levels and uncertainty may explain the generally poor results of participants for identifying the smallest attribute node (A_{min}) and the least certain node (U_{min}) (Fig. 5). As visual representations of uncertainty often aim to communicate relative levels of uncertainty [3], these poor results are somewhat disconcerting. The visualization shown to users was static, limiting ease of comparison. An interactive system, e.g. with hover or click-based details, could aid comparison of uncertainty levels and boost user confidence.

Effort. As observed by Lundström et al. [19], animation (for the purposes of uncertainty animation) caused more visual fatigue owing to the "movement and flickering of the image". However, when looking at the number of comments left by users regarding the *cognitive load*, wiggliness (W: [−11, +1]) fared equivalently to the other three representations (E: [−13, +3], F: [−8, +2], S: [−15, +5]). Regarding wiggliness' cognitive load, one participant did write that "*[wiggliness was an] information overload.*", while another commented that "*There was a lot going on to focus on which can make decision making difficult [...]*". Interestingly, negatively coded utterances regarding the cognitive load for the other three uncertainty encodings were less specific, describing their experiences generally as "*hard*", "*tough*", or "*difficult*". We also noted no meaningful differences in the perceived *physical effect* (E: −1, F: −0, S: −1, W: −2). However, one participant, in line with Lundström et al.'s [19] observations, did explicitly mention that wiggliness proved to be "*[...] straining on the eyes.*". Here, we speculate, based on other qualitatively coded utterances, that participants (unfamiliar with network visualizations) were already overwhelmed by the complexity of the graph's topology (discussed next), meaning the uncertainty encoding itself did not add any notable additional cognitive load or physical effort. Here, it is worth asking whether a larger and more complex network, with more complex patterns of node attribute uncertainty, could have revealed differences in the effort required as well as the physical effect on users. A graph of hundreds of nodes, each wiggling at different rates, could indeed prove taxing to parse visually.

Topology. Utterances related to *node placement* and *edge placement* described the ease or difficulty with which users were able to parse the topology of the presented graph. Comments were mostly negative across all four representations, for both node (E: −9, S: [−2, +1]) and edge placement(E: −8, F: −5, S: [−7, +1], W: −5). Interestingly, enclosure was the only uncertainty encoding with many negative comments relating to node placement. However, making sense of the edges in the drawing was generally regarded as challenging, i.e. negative. In the case of wiggliness specifically, one participant expressed the difficulty they experienced given the constant movement of the edges. In the case of fuzziness, one participant remarked that the fuzzy border made it difficult to determine whether an edge was or was not incident to a particular node. A denser graph, i.e. a graph with more edges, and subsequently more edge movement per frame, would probably make parsing the graph's topology even more challenging. It is thus worth asking whether, in the context of topological analyses of networks, animated wiggliness would be best suited for either smaller graphs or subgraph views only.

6. Limitations and future work

Many roads to rome. In this paper, based on the findings of our literature survey (Section 3.1), we focused explicitly on three non-animated visual encodings of uncertainty: saturation (S), enclosure (E), and fuzziness (F). However, as made clear in Fig. 2, many other possible (static) representations of uncertainty present themselves, such as color hue, direct text labels, or opacity. It is hence important to note that our evaluation of wiggliness is by no means exhaustive. Follow-up studies should additionally investigate and compare such visual channels in order to more completely gauge the effectiveness of these representations for uncertainty visualization in networks.

Investigating intricate interactions. In this paper, we focused on the visualization of one node attribute and its attached uncertainty in isolation. However, in real (domain-specific) applications, a visualization may need to visually map not simply one but multiple node attributes to various visual channels. Additionally, each of these attributes may bring with it its own uncertainty. Alternatively, a single attribute may have multiple (types of) uncertainties attached to it. In such cases, the interaction between these selected visual channels becomes important. For example, the use of node fuzziness may make understanding node shape difficult. Alternatively, the use of node brightness may complicate a user's understanding of node color. Here, it is worth asking whether and how wiggliness interacts with other common visual channels.

A loaded question. In this study, we made an effort to thoroughly investigate both user performance and experience from a quantitative and qualitative perspective. However, one aspect that has not been explicitly investigated was the cognitive task load of these individual uncertainty visualizations. According to past studies, though not our own qualitative results, animated wiggliness should conceptually result in a greater cognitive load compared to static representations. Future work should investigate the effect of representation on (cognitive) task load explicitly, using, for example, NASA's TLX [104], to better understand when and how to use them. Additionally, future work could combine task-based user studies with eye-tracking inn order to understand where a user focuses their attention.

Task and data complexity. In this study, we deliberately focused on simple, low-level graph analysis tasks and small, abstract networks to evaluate the baseline effectiveness of wiggliness as an uncertainty encoding. While our results suggest that wiggliness can be a conceptually useful approach in these controlled settings, future work must explore its applicability under greater complexity—both in task demands and data scale. For example, domain-specific tasks such as identifying the most certain paths or clusters may reveal different strengths or limitations of wiggliness. Likewise, larger and denser graphs introduce new challenges: as visual complexity increases, wiggliness may either become imperceptible or introduce excessive node occlusion due to increased spatial demands. Understanding how uncertainty visualizations scale with data and task complexity is essential to their broader adoption in real-world applications.

7. Conclusion

In this paper, we studied the impact of animated wiggliness for node attribute uncertainty visualization on user performance and experience in a mixed methods setup in a large-scale, crowd-sourced user study of 160 participants. Despite animation's infrequent use and recommendation in literature, we find animated wiggliness to perform equivalently to saturation, enclosure, and fuzziness. Interestingly, when investigating qualitative feedback received from participants, we find that, at least for the comparably simple datasets and tasks presented here, wiggliness is as learnable, intuitive, and understandable as all other investigated representations. We do, however, note several comments by users that hint at wiggliness' possible shortcomings, such as inducing visual fatigue and being poorly readable in certain situations. These shortcomings may limit wiggliness' utility for larger and more complex graphs and tasks. Nonetheless, the results of this study point towards the potential utility of wiggliness for uncertainty visualization in networks. In future work, we aim to investigate the efficacy of animated wiggliness in larger and denser networks in order to evaluate the approach's scalability and utility in practice.

CRediT authorship contribution statement

Henry Ehlers: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Daniel Pahr:** Writing – review & editing, Validation, Methodology, Conceptualization. **Sara di Bartolomeo:** Writing – review & editing, Validation, Methodology, Conceptualization. **Velitchko Filipov:** Writing – review & editing, Software, Methodology, Conceptualization. **Hsiang-Yun Wu:** Supervision, Writing – review & editing. **Renata G. Raidou:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cag.2025.104290.

Data availability

Data will be made available on request.

References

[1] Pang AT, Wittenbrink CM, Lodha SK. Approaches to uncertainty visualization. Vis Comput 1997;13(8):370–90. http://dx.doi.org/10.1007/s003710050111.
[2] Padilla L, Kay M, Hullman J. Uncertainty Visualization. OSF; 2020, http://dx.doi.org/10.31234/osf.io/ebd6r.
[3] Collins C, Carpendale S, Penn G. Visualization of Uncertainty in Lattices to Support Decision-Making. In: IEEE-VGTC symposium on visualization. The Eurographics Association; 2007, p. 51–8.
[4] Cox J, House D, Lindell M. Visualizing uncertainty in predicted hurricane tracks. Int J Uncertain Quantif 2013;3(2). http://dx.doi.org/10.1615/Int.J.UncertaintyQuantification.2012003966.
[5] Herring J, VanDyke MS, Cummins RG, Melton F. Communicating Local Climate Risks Online Through an Interactive Data Visualization. Environ Commun 2017;11(1):90–105. http://dx.doi.org/10.1080/17524032.2016.1176946.
[6] He C, Micallef L, Tanoli Z-u-R, Kaski S, Aittokallio T, Jacucci G. MediSyn: uncertainty-aware visualization of multiple biomedical datasets to support drug treatment selection. BMC Bioinformatics 2017;18(10):393. http://dx.doi.org/10.1186/s12859-017-1785-7.
[7] Hullman J. Why Authors Don't Visualize Uncertainty. IEEE Trans Vis Comput Graphics 2020;26(1):130–9. http://dx.doi.org/10.1109/TVCG.2019.2934287.
[8] Conroy M, Gillmann C, Harvey F, Mchedlidze T, Fabrikant SI, Windhager F, et al. Uncertainty in humanities network visualization. Front Commun 2024;8. http://dx.doi.org/10.3389/fcomm.2023.1305137.
[9] Yan K, Cui W. Visualizing the uncertainty induced by graph layout algorithms. In: 2017 IEEE Pacific visualization symposium (Pacificvis). 2017, p. 200–9. http://dx.doi.org/10.1109/PACIFICVIS.2017.8031595.
[10] Schulz C, Nocaj A, Goertler J, Deussen O, Brandes U, Weiskopf D. Probabilistic Graph Layout for Uncertain Network Visualization. IEEE Trans Vis Comput Graphics 2017;23(1):531–40. http://dx.doi.org/10.1109/TVCG.2016.2598919.
[11] Schwank J, Schöffel S, Stärz J, Ebert A. Visualizing Uncertainty of Edge Attributes in Node-Link Diagrams. In: 2016 20th international conference information visualisation (IV). 2016, p. 45–50. http://dx.doi.org/10.1109/IV.2016.19.
[12] Schwank J, Schöffel S. Visualizing Uncertainty in Node-Link Diagrams - a User Study. In: Ahram T, Falcão C, editors. Advances in usability and user experience. Cham: Springer International Publishing; 2018, p. 495–507. http://dx.doi.org/10.1007/978-3-319-60492-3_47.
[13] Vehlow C, Hasenauer J, Kramer A, Heinrich J, Radde N, Allgöwer F, et al. Uncertainty-aware visual analysis of biochemical reaction networks. In: 2012 IEEE symposium on biological data visualization (bioVis). 2012, p. 91–8. http://dx.doi.org/10.1109/BioVis.2012.6378598.
[14] Nobre C, Meyer M, Streit M, Lex A. The State of the Art in Visualizing Multivariate Networks. Comput Graph Forum 2019;38(3):807–32. http://dx.doi.org/10.1111/cgf.13728.
[15] Bonneau GP, Hege HC, Johnson CR, Oliveira MM, Potter K, Rheingans P, et al. Overview and State-of-the-Art of Uncertainty Visualization. In: Hansen CD, Chen M, Johnson CR, Kaufman AE, Hagen H, editors. Scientific visualization: uncertainty, multifield, biomedical, and scalable visualization. Mathematics and visualization, London: Springer; 2014, p. 3–27.
[16] Bartram L, Ware C, Calvert T. Moving Icons, Detection and Distraction. Interact 2001.
[17] Thompson J, Liu Z, Li W, Stasko J. Understanding the Design Space and Authoring Paradigms for Animated Data Graphics. Comput Graph Forum 2020;39(3):207–18. http://dx.doi.org/10.1111/cgf.13974.
[18] Tversky BR, Morrison JB, Betrancourt M. Animation: can it facilitate? Int J Hum-Comput Stud 2002;57(4):247–62. http://dx.doi.org/10.1006/ijhc.2002.1017.
[19] Lundström C, Ljung P, Persson A, Ynnerman A. Uncertainty Visualization in Medical Volume Rendering Using Probabilistic Animation. IEEE Trans Vis Comput Graphics 2007;13(6):1648–55. http://dx.doi.org/10.1109/TVCG.2007.70518.
[20] Brown R. Animated visual vibrations as an uncertainty visualisation technique. In: Proceedings of the 2nd international conference on computer graphics and interactive techniques in australasia and south east Asia. New York, NY, USA: Association for Computing Machinery; 2004, p. 84–9. http://dx.doi.org/10.1145/988834.988849.
[21] Byška J, Trautner T, Marques S, Damborský J, Kozlíková B, Waldner M. Analysis of Long Molecular Dynamics Simulations Using Interactive Focus+Context Visualization. Comput Graph Forum 2019;38(3):441–53. http://dx.doi.org/10.1111/cgf.13701.
[22] Wang Y, Shen Q, Archambault D, Zhou Z, Zhu M, Yang S, et al. AmbiguityVis: Visualization of Ambiguity in Graph Layouts. IEEE Trans Vis Comput Graphics 2016;22(1):359–68. http://dx.doi.org/10.1109/TVCG.2015.2467691.

[23] Vosough Z, Kammer D, Keck M, Groh R. Visualizing uncertainty in flow diagrams: a case study in product costing. In: Proceedings of the 10th international symposium on visual information communication and interaction. New York, NY, USA: Association for Computing Machinery; 2017, p. 1–8. http://dx.doi.org/10.1145/3105971.3105972.

[24] Vosough Z, Kammer D, Keck M, Groh R. Visualization approaches for understanding uncertainty in flow diagrams. J Comput Lang 2019;52:44–54. http://dx.doi.org/10.1016/j.cola.2019.03.002.

[25] Guo H, Huang J, Laidlaw DH. Representing Uncertainty in Graph Edges: An Evaluation of Paired Visual Variables. IEEE Trans Vis Comput Graphics 2015;21(10):1173–86. http://dx.doi.org/10.1109/TVCG.2015.2424872.

[26] Cesario N, Pang A, Singh L. Visualizing node attribute uncertainty in graphs. In: Visualization and data analysis 2011, vol. 7868, SPIE; 2011, p. 169–81. http://dx.doi.org/10.1117/12.872677.

[27] Preim B, Meuschke M. A survey of medical animations. Comput Graph 2020;90:145–68. http://dx.doi.org/10.1016/j.cag.2020.06.003.

[28] Blenkinsop S, Fisher P, Bastin L, Wood J. Evaluating the Perception of Uncertainty in Alternative Visualization Strategies. Cartographica 2000;37(1):1–14. http://dx.doi.org/10.3138/3645-4V22-0M23-3T52.

[29] Akiba H, Wang C, Ma K-L. AniViz: A template-based animation tool for volume visualization. IEEE Comput Graph Appl 2010;30(5):61–71. http://dx.doi.org/10.1109/MCG.2009.107.

[30] Kale A, Nguyen F, Kay M, Hullman J. Hypothetical Outcome Plots Help Untrained Observers Judge Trends in Ambiguous Data. IEEE Trans Vis Comput Graphics 2019;25(1):892–902. http://dx.doi.org/10.1109/TVCG.2018.2864909.

[31] Ma J, Chen J, Chen L, Jin L, Qin X. Dynamic Visualization of Uncertainties in Medical Feature of Interest. IEEE Access 2020;8:119170–83. http://dx.doi.org/10.1109/ACCESS.2020.3005399.

[32] Hermosilla P, Brecheisen R, Vázquez P-P, Vilanova A. Uncertainty visualization of brain fibers. The Eurographics Association; 2012, http://dx.doi.org/10.2312/LOCALCHAPTEREVENTS/CEIG/CEIG12/031-040.

[33] Zhang H, Qu D, Liu Q, Shang Q, Hou Y, Shen HW. Uncertainty visualization for variable associations analysis. Vis Comput 2018;34(4):531–49. http://dx.doi.org/10.1007/s00371-017-1359-8.

[34] Moody J, McFarland D, Bender-deMoll S. Dynamic Network Visualization. Am J Sociol 2005;110(4):1206–41. http://dx.doi.org/10.1086/421509.

[35] Beck F, Burch M, Diehl S, Weiskopf D. The State of the Art in Visualizing Dynamic Graphs. In: euroVis (sTARs). 2014.

[36] Forrester D, Kobourov SG, Navabi A, Wampler K, Yee GV. Graphael: A System for Generalized Force-Directed Layouts. In: Pach J, editor. Graph drawing. Berlin, Heidelberg: Springer; 2005, p. 454–64. http://dx.doi.org/10.1007/978-3-540-31843-9_47.

[37] Erten C, Harding PJ, Kobourov SG, Wampler K, Yee G. GraphAEL: Graph Animations with Evolving Layouts. In: Liotta G, editor. Graph drawing. Berlin, Heidelberg: Springer; 2004, p. 98–110. http://dx.doi.org/10.1007/978-3-540-24595-7_9.

[38] Baur M, Schank T. Dynamic Graph Drawing in Visone. 2008.

[39] Robertson G, Fernandez R, Fisher D, Lee B, Stasko J. Effectiveness of Animation in Trend Visualization. IEEE Trans Vis Comput Graphics 2008;14(6):1325–32. http://dx.doi.org/10.1109/TVCG.2008.125.

[40] Archambault D, Purchase H, Pinaud B. Animation, Small Multiples, and the Effect of Mental Map Preservation in Dynamic Graphs. IEEE Trans Vis Comput Graphics 2011;17(4):539–52. http://dx.doi.org/10.1109/TVCG.2010.78.

[41] Farrugia M, Quigley A. Effective Temporal Graph Layout: A Comparative Study of Animation versus Static Display Methods. Inf Vis 2011;10(1):47–64. http://dx.doi.org/10.1057/ivs.2010.10.

[42] Saraiya P, Lee P, North C. Visualization of graphs with associated timeseries data. In: IEEE symposium on information visualization, 2005. INFOVIS 2005.. 2005, p. 225–32. http://dx.doi.org/10.1109/INFVIS.2005.1532151.

[43] Boyandin I, Bertini E, Lalanne D. A Qualitative Study on the Exploration of Temporal Changes in Flow Maps with Animation and Small-Multiples. Comput Graph Forum 2012;31(3pt2):1005–14. http://dx.doi.org/10.1111/j.1467-8659.2012.03093.x.

[44] Jena A, Engelke U, Dwyer T, Raiamanickam V, Paris C. Uncertainty Visualisation: An Interactive Visual Survey. In: 2020 IEEE Pacific visualization symposium (Pacificvis). 2020, p. 201–5. http://dx.doi.org/10.1109/PacificVis48177.2020.1014.

[45] Potter K. Uncertainty Visualization and Data References. 2013.

[46] Hullman J, Qiao X, Correll M, Kale A, Kay M. In Pursuit of Error: A Survey of Uncertainty Visualization Evaluation. IEEE Trans Vis Comput Graphics 2019;25(1):903–13. http://dx.doi.org/10.1109/TVCG.2018.2864889.

[47] Weiskopf D. Uncertainty Visualization: Concepts, Methods, and Applications in Biological Data Visualization. Front Bioinform 2022;2. http://dx.doi.org/10.3389/fbinf.2022.793819.

[48] Griethe H, Schumann H. The Visualization of Uncertain Data: Methods and Problems. In: Simulation und visualisierung. 2006.

[49] Potter K, Rosen P, Johnson CR. From Quantification to Visualization: A Taxonomy of Uncertainty Visualization Approaches. In: Dienstfrey AM, Boisvert RF, editors. Uncertainty quantification in scientific computing. Berlin, Heidelberg: Springer; 2012, p. 226–49. http://dx.doi.org/10.1007/978-3-642-32677-6_15.

[50] MacEachren AM, Roth RE, O'Brien J, Li B, Swingley D, Gahegan M. Visual Semiotics & Uncertainty Visualization: An Empirical Study. IEEE Trans Vis Comput Graphics 2012;18(12):2496–505. http://dx.doi.org/10.1109/TVCG.2012.279.

[51] Kamal A, Dhakal P, Javaid AY, Devabhaktuni VK, Kaur D, Zaientz J, Marinier R. Recent advances and challenges in uncertainty visualization: a survey. J Vis 2021;24(5):861–90. http://dx.doi.org/10.1007/s12650-021-00755-1.

[52] Rhodes PJ, Laramee RS, Bergeron RD, Sparr TM. Uncertainty Visualization Methods in Isosurface Rendering. In: Eurographics (short presentations). 2003.

[53] MacEachren AM, Robinson A, Hopper S, Gardner S, Murray R, Gahegan M, et al. Visualizing Geospatial Information Uncertainty: What We Know and What We Need to Know. Cartogr Geogr Inf Sci 2005;32(3):139–60. http://dx.doi.org/10.1559/1523040054738936.

[54] Jiang B, Ormeling O, Kainz W. Visualization Support for Fuzzy Spatial Analysis. In: Auto carto 12, charlotte, north carolina. 1995, p. 291–300.

[55] Grigoryan G, Rheingans P. Point-based probabilistic surfaces to show surface uncertainty. IEEE Trans Vis Comput Graphics 2004;10(5):564–73. http://dx.doi.org/10.1109/TVCG.2004.30.

[56] Hengl T. Visualisation of uncertainty using the HSI colour model: computations with colours. In: Proceedings of the 7th international conference on geoComputation. 2003, p. 8–17.

[57] Boukhelifa N, Bezerianos A, Isenberg T, Fekete J-D. Evaluating Sketchiness as a Visual Variable for the Depiction of Qualitative Uncertainty. IEEE Trans Vis Comput Graphics 2012;18(12):2769–78. http://dx.doi.org/10.1109/TVCG.2012.220.

[58] Howard D, MacEachren AM. Interface Design for Geographic Visualization: Tools for Representing Reliability. Cartogr Geogr Inf Syst 1996;23(2):59–77. http://dx.doi.org/10.1559/152304096782562109.

[59] McKenzie G, Hegarty M, Barrett T, Goodchild M. Assessing the effectiveness of different visualizations for judgments of positional uncertainty. Int J Geogr Inf Sci 2016;30(2):221–39. http://dx.doi.org/10.1080/13658816.2015.1082566.

[60] Correll M, Moritz D, Heer J. Value-Suppressing Uncertainty Palettes. In: Proceedings of the 2018 CHI conference on human factors in computing systems. New York, NY, USA: Association for Computing Machinery; 2018, p. 1–11. http://dx.doi.org/10.1145/3173574.3174216.

[61] Kniss JM. Managing uncertainty in visualization and analysis of medical data. In: 2008 5th IEEE international symposium on biomedical imaging: from nano to macro. 2008, p. 832–5. http://dx.doi.org/10.1109/ISBI.2008.4541125.

[62] Lowell K, Christy B, Benke K, Day G. Modelling fundamentals and the quantification and spatial presentation of uncertainty. J Spat Sci 2011;56(2):185–201.

[63] Zier B, Atsushi I. Fuzzy Relational Visualization for Decision Support. Tech. Rep., 2011, p. 8–15.

[64] Padilla LM, Hansen G, Ruginski IT, Kramer HS, Thompson WB, Creem-Regehr SH. The influence of different graphical displays on nonexpert decision making under uncertainty.. J Exp Psychol: Appl 2015;21(1):37–46. http://dx.doi.org/10.1037/xap0000037.

[65] Gschwandtnei T, Bögl M, Federico P, Miksch S. Visual Encodings of Temporal Uncertainty: A Comparative User Study. IEEE Trans Vis Comput Graphics 2016;22(1):539–48. http://dx.doi.org/10.1109/TVCG.2015.2467752.

[66] Munzner T. Visualization Analysis and Design. CRC Press; 2014.

[67] Garlandini S, Fabrikant SI. Evaluating the Effectiveness and Efficiency of Visual Variables for Geographic Information Visualization. In: Hornsby KS, Claramunt C, Denis M, Ligozat G, editors. Spatial information theory. Berlin, Heidelberg: Springer; 2009, p. 195–211. http://dx.doi.org/10.1007/978-3-642-03832-7_12.

[68] Scholz RW, Lu Y. Uncertainty in Geographic Data on Bivariate Maps: An Examination of Visualization Preference and Decision Making. ISPRS Int J Geo-Inf 2014;3(4):1180–97. http://dx.doi.org/10.3390/ijgi3041180.

[69] Sanyal J, Zhang S, Bhattacharya G, Amburn P, Moorhead R. A User Study to Compare Four Uncertainty Visualization Methods for 1D and 2D Datasets. IEEE Trans Vis Comput Graphics 2009;15(6):1209–18. http://dx.doi.org/10.1109/TVCG.2009.114.

[70] Brecheisen R, Vilanova A, Platel B, ter Haar Romeny B. Parameter Sensitivity Visualization for DTI Fiber Tracking. IEEE Trans Vis Comput Graphics 2009;15(6):1441–8. http://dx.doi.org/10.1109/TVCG.2009.170.

[71] Fout N, Ma K-L. Fuzzy Volume Rendering. IEEE Trans Vis Comput Graphics 2012;18(12):2335–44. http://dx.doi.org/10.1109/TVCG.2012.227.

[72] Tak S, Toet A, van Erp J. The Perception of Visual UncertaintyRepresentation by Non-Experts. IEEE Trans Vis Comput Graphics 2014;20(6):935–43. http://dx.doi.org/10.1109/TVCG.2013.247.

[73] Correll M, Gleicher M. Error Bars Considered Harmful: Exploring Alternate Encodings for Mean and Error. IEEE Trans Vis Comput Graphics 2014;20(12):2142–51. http://dx.doi.org/10.1109/TVCG.2014.2346298.

[74] Guo Y, Esfahani F, Shao X, Srinivasan V, Thomo A, Xing L, et al. Integrative COVID-19 biological network inference with probabilistic core decomposition. Brief Bioinform 2022;23(1):bbab455. http://dx.doi.org/10.1093/bib/bbab455.

[75] Borgo R, Kehrer J, Chung DHS, Maguire E, Laramee RS, Hauser H, et al. Glyph-based Visualization: Foundations, Design Guidelines, Techniques and Applications. The Eurographics Association; 2012, http://dx.doi.org/10.2312/CONF/EG2013/STARS/039-063.

[76] Rousseeuw PJ, Ruts I, Tukey JW. The Bagplot: A Bivariate Boxplot. Amer Statist 1999;53(4):382–7. http://dx.doi.org/10.1080/00031305.1999.10474494.

[77] Greis M, Ohler T, Henze N, Schmidt A. Investigating Representation Alternatives for Communicating Uncertainty to Non-experts. In: Abascal J, Barbosa S, Fetter M, Gross T, Palanque P, Winckler M, editors. Human-computer interaction – INTERACT 2015. Cham: Springer International Publishing; 2015, p. 256–63. http://dx.doi.org/10.1007/978-3-319-22723-8_21.

[78] Sanyal J, Zhang S, Dyer J, Mercer A, Amburn P, Moorhead R. Noodles: A Tool for Visualization of Numerical Weather Model Ensemble Uncertainty. IEEE Trans Vis Comput Graphics 2010;16(6):1421–30. http://dx.doi.org/10.1109/TVCG.2010.181.

[79] Ehlschlaeger CR, Shortridge AM, Goodchild MF. Visualizing spatial data uncertainty using animation. In: Exploratory cartograpic visualisation, Comput Geosci In: Exploratory cartograpic visualisation, 1997;23(4):387–95.http://dx.doi.org/10.1016/S0098-3004(97)00005-8,

[80] Zhang D, Adar E, Hullman J. Visualizing Uncertainty in Probabilistic Graphs with Network Hypothetical Outcome Plots (NetHOPs). IEEE Trans Vis Comput Graphics 2022;28(1):443–53. http://dx.doi.org/10.1109/TVCG.2021.3114679.

[81] Bostock M, Ogievetsky V, Heer J. D^3 Data-Driven Documents. IEEE Trans Vis Comput Graphics 2011;17(12):2301–9. http://dx.doi.org/10.1109/TVCG.2011.185.

[82] Schnotz W, Rasch T. Enabling, facilitating, and inhibiting effects of animations in multimedia learning: Why reduction of cognitive load can have negative results on learning. Educ Technol Res Dev 2005;53(3):47–58. http://dx.doi.org/10.1007/BF02504797.

[83] Stasko J, Badre A, Lewis C. Do algorithm animations assist learning? an empirical study and analysis. In: Proceedings of the INTERACT '93 and CHI '93 conference on human factors in computing systems. New York, NY, USA: Association for Computing Machinery; 1993, p. 61–6. http://dx.doi.org/10.1145/169059.169078.

[84] Ehlers H, Pahr D, Filipov V, Wu H-Y, Raidou RG. Me! Me! Me! Me! a study and comparison of ego network representations. Comput Graph 2024;125:104123. http://dx.doi.org/10.1016/j.cag.2024.104123.

[85] Broido AD, Clauset A. Scale-free networks are rare. Nat Commun 2019;10(1):1017. http://dx.doi.org/10.1038/s41467-019-08746-5.

[86] Yoghourdjian V, Archambault D, Diehl S, Dwyer T, Klein K, Purchase HC, et al. Exploring the limits of complexity: A survey of empirical studies on graph visualisation. Vis Informatics 2018;2(4):264–82. http://dx.doi.org/10.1016/j.visinf.2018.12.006.

[87] Rossi RA, Nesreen KA. The Network Data Repository with Interactive Graph Analytics and Visualization. In: AAAI. first ed.. vol. 29, 2015.

[88] Mersch DP, Crespi A, Keller L. Tracking individuals shows spatial fidelity is a key regulator of ant social organization. Science 2013;340(6136):1090–3.

[89] Koutrouli M, Karatzas E, Paez-Espino D, Pavlopoulos GA. A Guide to Conquer the Biological Network Era Using Graph Theory. Front Bioeng Biotechnol 2020;8:34, 10/ggm3qc.

[90] Quevillon LE. Social, spatial, and temporal organization in a complex insect society. Sci Rep 2015;5.

[91] Nobre C, Wootton D, Harrison L, Lex A. Evaluating Multivariate Network Visualization Techniques Using a Validated Design and Crowdsourcing Approach. In: Proceedings of the 2020 CHI conference on human factors in computing systems. New York, NY, USA: Association for Computing Machinery; 2020, p. 1–12. http://dx.doi.org/10.1145/3313831.3376381.

[92] Lam H, Bertini E, Isenberg P, Plaisant C, Carpendale S. Seven Guiding Scenarios for Information Visualization Evaluation Tech. Rep., (hal- 00723057). 2011.

[93] Ghoniem M, Fekete JD, Castagliola P. A Comparison of the Readability of Graphs Using Node-Link and Matrix-Based Representations. In: IEEE symposium on information visualization. 2004, p. 17–24. http://dx.doi.org/10.1109/INFVIS.2004.1.

[94] Ghoniem M, Fekete JD, Castagliola P. On the Readability of Graphs Using Node-Link and Matrix-Based Representations: A Controlled Experiment and Statistical Analysis. Inf Vis 2005;4(2):114–35. http://dx.doi.org/10.1057/palgrave.ivs.9500092.

[95] Lee B, Plaisant C, Parr CS, Fekete JD, Henry N. Task taxonomy for graph visualization. In: Proceedings of the 2006 AVI workshop on beyond time and errors: novel evaluation methods for information visualization. New York, NY, USA: Association for Computing Machinery; 2006, p. 1–5. http://dx.doi.org/10.1145/1168149.1168168.

[96] Amar R, Eagan J, Stasko J. Low-level components of analytic activity in information visualization. In: IEEE symposium on information visualization, 2005. INFOVIS 2005.. 2005, p. 111–7. http://dx.doi.org/10.1109/INFVIS.2005.1532136.

[97] Wobbrock JO, Findlater L, Gergle D, Higgins JJ. The aligned rank transform for nonparametric factorial analyses using only anova procedures. In: Proceedings of the SIGCHI conference on human factors in computing systems. New York, NY, USA: Association for Computing Machinery; 2011, p. 143–6. http://dx.doi.org/10.1145/1978942.1978963.

[98] Elkin LA, Kay M, Higgins JJ, Wobbrock JO. An Aligned Rank Transform Procedure for Multifactor Contrast Tests. In: The 34th annual ACM symposium on user interface software and technology. New York, NY, USA: Association for Computing Machinery; 2021, p. 754–68. http://dx.doi.org/10.1145/3472749.3474784.

[99] Chi MT. Quantifying Qualitative Analyses of Verbal Data: A Practical Guide. J Learn Sci 1997;6(3):271–315. http://dx.doi.org/10.1207/s15327809jls0603_1.

[100] Prolific. London, UK: Prolific; 2014, URL https://www.prolific.com.

[101] Cedilnik A, Rheingans P. Procedural annotation of uncertain information. In: Proceedings visualization 2000. VIS 2000 (cat. no.00CH37145). 2000, p. 77–84. http://dx.doi.org/10.1109/VISUAL.2000.885679.

[102] Ware C. Lightness, Brightness, Contrast, and Constancy. In: Ware C, editor. Information visualization (fourth edition). Interactive technologies, Morgan Kaufmann; 2021, p. 69–94.

[103] Heer J, Robertson G. Animated Transitions in Statistical Data Graphics. IEEE Trans Vis Comput Graphics 2007;13(6):1240–7. http://dx.doi.org/10.1109/TVCG.2007.70539.

[104] Hart SG, Staveland LE. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In: Hancock PA, Meshkati N, editors. Advances in psychology. Human mental workload, vol. 52, North-Holland; 1988, p. 139–83.