Effect of white matter uncertainty visualization in neurosurgical decision making

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Abstract—Fiber tracking is a powerful technique that provides insight into the brain's white matter structure. Despite its potential, the inherent uncertainties limit its widespread clinical use. These uncertainties potentially hamper the clinical decisions neurosurgeons have to make before, during, and after the surgery. Many techniques have been developed to visualize uncertainties, however, there is limited evidence to suggest whether these uncertainty visualization influences neurosurgical decision-making. In this paper, we evaluate the hypothesis that uncertainty visualization in fiber tracking influences neurosurgeon's decisions and confidence in their decisions. For this purpose, we designed a user study through an online interactive questionnaire and evaluate the influence of uncertainty visualization in neurosurgical decision-making. The results of this study emphasize the importance of uncertainty visualization in clinical decision making by highlighting the influence of different intervals of uncertainty visualization in critical clinical decisions.

In most clinical workflows, it is common practice to explore, analyze, and make decisions based on the vast amount of pre-processed and transformed data. During the processing, transformation, or even in the graphical representation of the results, uncertainties can be introduced. These inherent uncertainties propagate throughout this pipeline and can adversely impact the accuracy of the results. For instance, consider a scenario where a patient's medical imaging scan is acquired and processed to identify the diameter of a blood vessel that is narrowing. Different sources of uncertainty affect the diameter computation. For example, the image acquisition itself adds noise, and the segmentation method adds human-defined parameters, such as thresholds. Due to different sources of errors, the resulting value for the diameter can be different at each computation. In this scenario, a statistical interpretation of the uncertain data, such as mean or median, can be used to estimate the diameter of the blood vessel. When doing so, it becomes crucial to incorporate the representation of the corresponding uncertainties when interpreting the results, especially from complex pipelines. Failure to do so may lead to inaccurate conclusions. Hullman[1] investigates the complexities involved in uncertainty visualization and explores how users tend to adopt risky behavior and ignore implicit or hidden decision criteria when uncertainty information is not presented. Even though the need for visualizing uncertainty associated with the results is widely accepted, actual use is limited. One of the main challenges is to include additional uncertainty information into an existing already complex visualization while maintaining comprehension.

In the neurosurgical workflow, knowledge of a patient's brain anatomy is vital for the surgeons, especially during the preoperative planning and intraoperative stages of brain tumor surgery. Fiber tracking, derived from Diffusion Tensor Imaging (DTI), is a non-invasive technique that allows the virtual reconstruction of anatomical connections of the brain, i.e., white matter. This process has proven to be a useful technique for the interpretation of brain anatomy[2]. Despite its potential[3], fiber tracking is not yet routinely used in clinical practice. This limited adoption is considered to be largely due to the significant amount of uncertainty present in the results[4].

Numerous techniques have been presented in the

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literature for visualizing uncertainties in the context of fiber tracking[5]. However, there are no studies to indicate how uncertainty visualization influences reasoning and decision-making. While some studies evaluate the impact of uncertainties on decision-making in general[6], extrapolating these results to the context of fiber tracking proves challenging. This difficulty arises due to the intricate task of representing uncertainty in complex objects like fiber tracts, which contrasts with the relative simplicity of handling uncertainty in scalar values like a vessel diameter.

In this paper, we address this gap by designing and implementing a user study that provides insights into whether the visualization of uncertainty in fiber tracking results can affect neurosurgical decision-making. To facilitate this study, we implemented a framework to visualize uncertainty information within a fiber tracking visualization, based on previous work[7]. We use this framework to embed interactive 3D views in an online questionnaire, allowing participants to explore and interact with the uncertainty visualization. This implementation ensured that our questionnaire was grounded in practical and clinically relevant scenarios, and provided the necessary information to answer the questionnaire. Drawing from the hypotheses presented by Padilla et al.[6], we hypothesize that the representation of uncertainty will influence participants' judgments, leading them to make more cautious decisions as the presented uncertainty increases. In this work, we use different confidence intervals to show such varying levels of uncertainty. To not confuse these with the confidence of participants in their decision, that we also want to test, we call them *uncertainty intervals* in the remainder of this paper. Accordingly, we have formulated the following hypotheses based on the role of uncertainty in decision making:

- **H1:** Visualization of uncertainty will influence the participants' decision.
- **H2:** Participants will make a more cautious decision when a larger uncertainty interval is visualized.
- **H3:** Confidence of the participants in decision-making will be affected by the uncertainty visualization.

Clinical Background

In this section, we introduce the basic concepts related to the neurosurgical aspects needed to understand the study. The most important aspects are the type of tumor used, i.e., Gliomas, and the process of clinical decision-making.

A glioma is the most common type of malignant brain tumor. Surgery is in many cases the preferred first step of treatment for gliomas, as the extent of resection is significantly related to overall survival. However, gliomas grow infiltratively into surrounding brain structures, and care must be taken not to damage nearby critical functional structures in order to avoid severe and permanent neurological deficits.

While MRI-based fiber tractography is commonly used as a non-invasive tool to analyze white matter fiber tracts before surgery, intraoperative neuromonitoring[8] (IONM) is considered the gold standard method to identify white matter tracts. White matter tracts are not visible when the brain tissue is directly inspected during tumor resection. IONM keeps the patient awake and, through electrical stimulation, allows the surgeon to identify whether specific fiber tracts are present. For example, the patient is asked to speak; if, with direct stimulation of the tissue, the patient experiences difficulties speaking, it indicates that the language tract is in the stimulated area and, therefore, should be avoided. Although it has been shown that IONM in an awake setting improves both the surgical extent of resection and postoperative neurological status, it adds discomfort and complexity to the procedure and is avoided if possible. However, it is currently not known which patients will benefit from IONM[9]. Generally speaking, when there is a margin between the tumor border and specific critical functional brain regions or tracts, surgeons will refrain from using IONM. However, this is a qualitative judgement: margins are seldom specified in the literature, and there is significant variability in decision-making between neurosurgeons even within a neurosurgical center.

Related Work

Uncertainty visualization

In numerous applications, including complex pipelines like clinical workflows and physical simulations, uncertainty in the results is inevitable. Griethe and Schumann[10] and Pang et al.[11] argue that error or uncertainty can be introduced in any step from the acquisition of the data when filtering or processing the data or when presenting the data to a user. Uncertainty can be understood as a composition of different concepts such as error, imprecision, subjectivity, and non-specificity[12]. Skeels et al.[13] further add that by developing effective ways of visualizing the uncertainty associated with data, we can help users better understand and appropriately use this data. However, as further stated by the authors, uncertainty is not always expressed as a quantifiable probability, especially when it involves

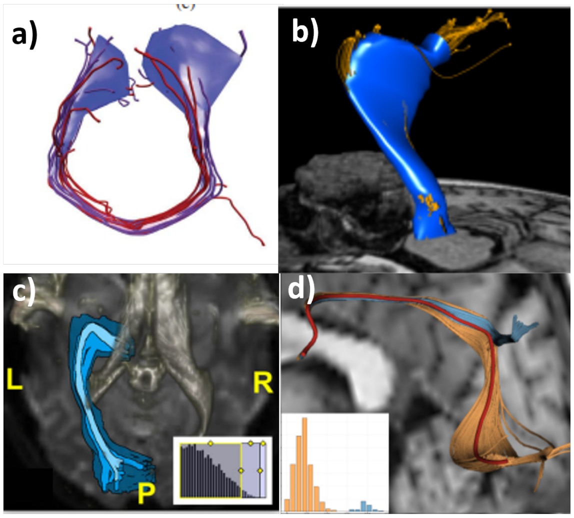

FIGURE 1. Different approaches to visualize statistical information in fiber ensembles by a) Mirzagar et al.[15], b) Enders et al.[16], c) Brecheisen et al.[17], and d) Siddiqui et al.[7]. Our study is based on the latter.

complex data representation, as in the case of fiber tracking, presented in this paper.

There has been considerable work on uncertainty visualization for scalar, vector, and tensor fields. For a general overview of uncertainty visualization specifically in Diffusion Tensor Imaging (DTI), we refer to recent surveys[4,14]. The visualization of uncertainties in fiber tracking poses unique challenges due to the intricate nature of neural pathways, susceptibility to noise, and the complex interplay of various factors influencing the accuracy of tracking algorithms.

To represent uncertainty within a fiber ensemble, statistical information, such as mean and uncertainty intervals, is of interest. However, these measures are not as well defined for curves as they are for scalar values. Several approaches to compute this statistical information for ensembles of curves exist. Mirzagar et al.[15] use the concept of band-depth to compute the centrality within the set of curves and estimate the variation (Figure 1a). Ender et al.[16] compute the average of the curves in a bundle, resulting in the central fiber (Figure 1b). Instead of computing the mean of the fibers, Brecheisen et al.[17] compute the median and uncertainty interval of the curve by calculating the distances among fiber pairs based on a chosen measure (Figure 1c). This approach enables the visualization of complex fiber structures along with the uncertainty information. Brecheisen used illustrative approach to visualize the uncertainty intervals projected on a slice. This technique gives information on uncertainty intervals, however, it doesn't provide the depth information of the uncertainty intervals in 3D. Siddiqui et al.[7], used the same approach to calculate uncertainty intervals and integrate this approach in interactive 3d visualization (Figure 1d). In this work, we utilize their visualization technique, as it closely resembles representations without uncertainty, familiar to clinicians for viewing fiber tracking results, requiring minimal additional effort for interpretation. We compute the most representative fiber (median fiber) and visualize varying uncertainty intervals. This visualization method also enables us to test our hypothesis, based on uncertainty intervals adopted from Padilla et al.[6] It should be noted that comparing uncertainty visualization methods is considered beyond the scope of this paper.

Decision making under uncertainty

Decision making is a common goal for visualization, yet Dimara et al.[18] suggested that visualization studies largely lack explicit ties to decision making. In uncertainty visualization, Hullman[1] presented the complexities in the effective communication of the uncertainty results and highlighted the risk if the results are not properly communicated. Although uncertainty visualization has a strong tradition of empirical research in visual design and user comprehension, research into the effectiveness of uncertainty visualization as it relates to decision support remains critical and an important area of work[19]. Researchers have emphasized the need for empirical research to test the effectiveness of visual representations of uncertainty and their usefulness in the decision-making process[20].

A few studies in the field of psychology showed that providing uncertainty information has a positive influence on decision-making. In a study conducted by Roulston et al.[21], participants made more accurate decisions when standard errors were presented in addition to a point estimate. Joslyn et al.[22] evaluated decision making when involving uncertainty in weather forecasts, and the results suggest that uncertainty information improved decision quality overall and increased trust in the forecast. Padilla et al.[6] evaluated participants' judgment in the presence of direct and indirect uncertainties. The results suggest that participants could incorporate the communicated uncertainty into their judgments relatively accurately. Similar results were observed in other application scenarios, such as weather forecasting[23] or flood forecasting[24]. However, some studies suggest that uncertainty visualization has little to no effect compared to decisions

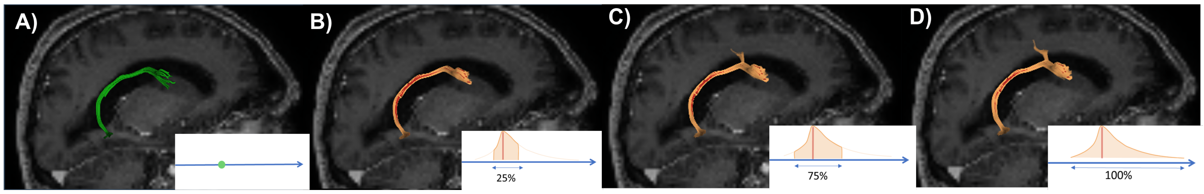

FIGURE 2. Uncertainty intervals for the Arcuate Fasciculus bundle. A) No uncertainty B) 25% interval visualization C) 75% interval visualization D) 100% interval visualization

made without uncertainty[25]. Overall, findings regarding the impact of uncertainty visualizations are varied, highlighting the substantial influence of visualization selection on comprehension.

Clinical decision-making is a unique process that involves the interplay between knowledge of pre-existing pathological conditions, explicit patient information, and the provided imaging data. Clinical decisions can have substantial consequences and involve many sources of uncertainties that may critically hamper the decision-making process. In a recent study, Gillmann et al.[26] provided a survey of uncertainty-aware visualization in medical imaging and emphasized the need for empirical research to analyze the effectiveness of the presented uncertainty visualization techniques. Galesic[27] presented icon arrays to communicate medical risk and the results suggested that this technique improved the accuracy of the understanding of the risk in wide range of patient groups. McDowell and Kause[28] investigated how different types of uncertainty in medical evidence affect perception when presented through tables, bar graphs, and icon arrays. They found that clear and well-designed displays of uncertainty did not negatively affect participants' understanding or trust in the information. This suggests that the way uncertainty is presented visually is more important than the specific type of uncertainty being communicated. To the best of our knowledge, there does not exist any research on the influence of uncertainty visualization in the decision making process that includes information from fiber tracking. In our work, we took inspiration from the studies on the effect of uncertainty visualization in decision-making from the field of psychology[6] and visualization[29] and designed our study to test the effectiveness and consequences of uncertainty visualization in neurosurgical decisions.

Study Design

We embraced the context as employed in the study by Padilla et al.[6], where the impact of uncertainty visualization on decision-making is evaluated on the weather forecaster by manipulating uncertainty intervals in the results and analyzing how the decisions are changing based on these presented uncertainties. Padilla et al.[6], showed participants the distribution of possible variations in temperature based on an artificial scenario and were tasked to make a decision. They found that participants made more informed and cautious decisions when uncertainty was shown. Based this work, we aim to analyze the impact of uncertainty visualization on clinical decision making, specifically when showing uncertainty for fiber tracking results.

We want to test whether the participants have taken uncertainty visualization into account (H1), they made a more cautious decision when uncertainty was visualized (H2), and to whether their confidence was influenced (H3). To do so, we present eight patient/uncertainty combinations to each participant in a mixed-design setup. For each patient, four different uncertainty intervals were created (see Figure 2 for one example patient), from which two are randomly drawn for each participant. Each participant sees all four different clinical cases or patients (see Figure 3). The resulting eight patient/uncertainty combinations are then shown to the participants in random order (Figure 4). This allows us to track changes for the decision for a patient within-participant, but general claims over all uncertainty levels can only be done between-participants. We performed a formative user study using an interactive online questionnaire presented to surgeons who use fiber tracking in their clinical workflow. The design of the user study was an iterative process involving multiple meetings and interviews with a panel of neurosurgeons.

Expert insights and initial interviews

During the initial design phase of the study, we conducted the first round of interview sessions with four oncology neurosurgeons and two researchers in neurosurgery to gain insights into their approach to analyze fiber tracking results and to identify specific scenarios where uncertainty visualization would

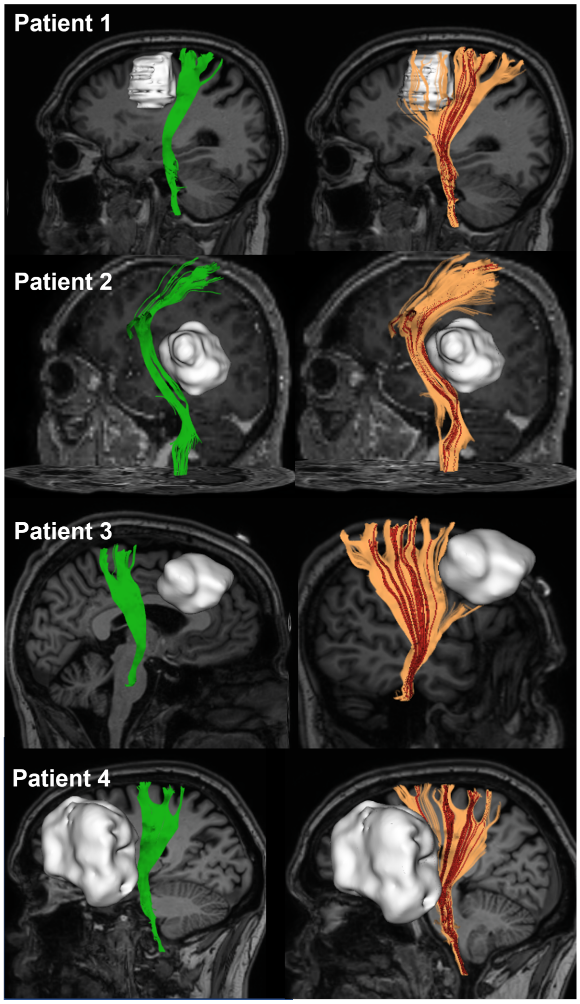

FIGURE 3. Cases of the four patient data sets used in the evaluation. Left: Fiber tracking results without uncertainty information. Right: Fiber tracking results with 100 % interval of uncertainty visualization

be relevant. We discussed how the resulting fiber tracts affect the neurosurgical decision-making process through semi-structured interviews. Decision making in neurosurgical context is complex. Different decisions are taking place and many factors beyond fiber tracking influence the decisions. We identify the scenarios, and the formulation of the questions such that the neurosurgeons answers would be focused on the fiber tracking uncertainty visualization and not in other external factors. For example, it was identified that the decision on IONM was the most appropriate for our purposes and that gliomas would be the type of tumors to study. The questionnaire was presented and refined in four feedback moments with our collaborators. During these feedback sessions, the information and interactions that should be provided to neurosurgeons to evaluate the cases were also discussed. Furthermore, together with the neurosurgeons and radiologists, we prepared clinically relevant data sets for the participants. The neurosurgeons suggested seven data sets from their past experiences, where fiber tracking results played an important role in decision-making. We prepared the results with uncertainty visualization which were discussed in the interactive sessions with the collaborators to select the most appropriate ones.

Fiber tracking and uncertainty computation

Our work involves assessing the impact of uncertainty on decision-making in brain tumor surgery where information from fiber tracking is available, regardless of the specific fiber tracking and uncertainty visualization techniques employed. For this purpose, the fiber ensembles were generated together with our collaborators. We followed the workflow that is currently used in their practice as close as possible. The fiber tracking process starts with the manual definition of the seed region from which the seed point for each fiber tract is drawn. In scenarios without uncertainty information, we employ deterministic fiber tracking[30], a widely utilized method in the standard clinical workflow. Conversely, when uncertainty information is integrated, we adopt the bootstrapping method[7]. The result of this process is an ensemble of tracts for each seed point, representing the possible variations for the corresponding fiber.

Uncertainty visualization

Without uncertainty, the fibers are visualized as green tubes, as shown in Figure 2A.

For the uncertainty visualization, we compute the median and uncertainty interval for each fiber by calculating the distances among fiber pairs based on a chosen measure, presented by Brecheisen et al.[17]. The median, termed as the representative fiber, is determined by considering the minimum accumulated distance to all the other fibers in the ensemble and, as such, can be seen as the most central fiber. In addition, all other fibers are ordered according to their distances to the representative fiber such that the uncertainty intervals can be defined on the resulting distribution. For example, a uncertainty interval of 25% includes the 25% fibers with lower distance to the representative fiber. For the visualization, the representative fibers are shown as red tubes, and the remaining fiber samples that correspond to the selected interval, as illuminated polylines in orange (Figure 2B-D). This is a simple visualization, similar to the standard representation our collaborators are used to, where all fibers corresponding to one interval are shown, indicating the uncertainty interval also visually. The visualization makes sure that the representative fiber is always visible by drawing it on top[7]. The uncertainty intervals can be selected to understand the distribution better. To cover a meaningful variety of uncertainty information we chose several different uncertainty intervals for inclusion in the questionnaire, originally based on quartiles, including 0% and 100%. At the same time, after discussion with our collaborators, it also became clear that we must keep the number of different uncertainty intervals small to not overburden participants with too many cases. Thus, we removed the 50% uncertainty interval to reduce the number of tests. As a result we ended up with three uncertainty intervals in addition to no uncertainty: 25%, 75%, and 100%, shown in Figures 2B, C, and D, respectively.

Patient cases

We chose four different anonymized patient datasets for testing our hypotheses shown in Figure 3 without uncertainty and with a 100% interval. Four cases were considered a good number to generalize from the nuances of each specific case. Given the complexity of the problem, more cases were seen as unfeasible. The cases were selected based on suggestions by our collaborating neurosurgeons. Specifically, we focus on cases where the tumor is present in the vicinity of the corticospinal tract, and the tracts are distorted with the presence of the tumor. This tract plays a critical role in motor functioning. Damage will very likely result in severe and permanent motor deficits. Neurosurgeons will not risk damaging the corticospinal tract to improve the extent of tumor resection. These cases were selected since for all of them it is not obvious, whether the procedure should be carried out using IONM or not. There is a balance of risks between full tumor resection and damage to the motor tract. Using IONM would be a conservative decision but it involves invasiveness and higher costs of the procedure. This means that it is not possible to know what is the correct choice before the procedure. I.e., there is no ground truth or correct answer. Note, testing for the correct answer is also not the goal of this study, but rather evaluating whether showing uncertainty has an impact in the decision making.

Patient/uncertainty combination

For each patient fiber tracking results are then prepared with the uncertainty intervals discussed above: no uncertainty 25% (Low interval), 75% (Medium interval), and 100% (High interval) as shown for one example in Figure 2. Combining the four patients with four uncertainty intervals creates a total of 16 cases. To not overburden the participants, we decided to draw eight pseudo-random cases to review for each participant in the study. As discussed above, each participant was presented with all four patients but only two randomly selected two uncertainty intervals per patient. Cases were shown in random order but the same patient was never shown consecutively to reduce further learning biases. The complete process is also illustrated in Figure 4. As a result, all participants had an equal opportunity to explore cases from all four patients with varying uncertainty intervals.

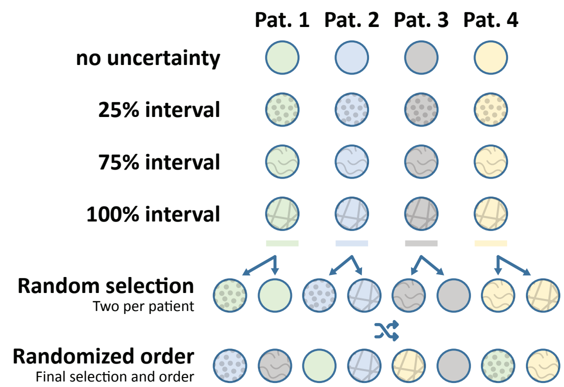

FIGURE 4. The distribution of the cases among participants.

Questionnaire

In this section, we discuss the process behind formulating the evaluation questionnaire and elaborate on its integration into the interactive web app designed for the evaluation[a].

Hypothesis driven question formulation

One of the main aspects of the design of the questionnaire are the questions to be asked per presented case. We aim at concrete question(s) that can be used to compare and analyze the decision making of the participants. We held a number of meetings with collaborators. Here, we discussed the surgeons' routine decisions during fiber tracking analysis. These vital choices involve diverse aspects, like planning tumor resection paths, deciding on sleep or awake surgery,

[a]The questionnaire can be accessed online and is open source on GitHub.

or utilizing Intraoperative Neurophysiological Monitoring (IONM) for surgical assistance, among others. It is important to note that these clinical decisions are also influenced by numerous other factors, including the patient's health condition, tumor type, preoperative counseling and patient preferences regarding the functional/oncological balance (operate more on the safe side or be more aggressive to maximize resection), and more. To mitigate their impact and isolate the influence of fiber tracking visualizations on decision-making, we provide the participants with specific clinical context conditions. We instructed participants, that the tumor should be assumed to be a glioma, and the patient is eligible for IONM/awake surgery, so no other factors influence the decision. We also emphasize that the quality of the generated fiber tracts and their anatomical representation is not part of the evaluation such that the answer does not diverge into the quality of the fiber tracking results or the used algorithm. It was advised by the neurosuregeons to pose only a single decision-making question per provided case to minimize the burden and potential study dropouts. Following the input from our collaborators, we defined the following main question:

> *Based on this visualization, will you recommend using Intraoperative Neurophysiological Monitoring (IONM) during the surgical procedure?*

The participant has to make a binary decision, either Yes or No, based on the provided uncertainty visualization case. Participants might be inclined to utilize Intraoperative Neuromonitoring (IONM) if they believe that the tumor resection process could impact the integrity of healthy fiber bundles and if they require additional assistance throughout the procedure.

Moreover, we ask the user an optional open question to comment on their decision to understand the reasoning behind their decisions.

> *Would you like to comment on your decision? You may want to comment, for instance, what arguments led you to this decision?*

After each question, participants were also asked about their confidence on a Likert scale ranging from 1 (not confident) to 5 (very confident):

> *How Confident are you about the decision?*

Interactive 3D web visualization

To be able to respond to the questions effectively based on the provided fiber tracking case results and uncertainty interval, 3D interaction with the results is necessary. We have added the needed interactions suggested by our collaborators such that the participants can effectively explore the fiber tracking and uncertainty results. The questionnaire was developed as a web application such that it could be distributed independently. In order to integrate the proposed interactions using VTKjs[31] and HTML. The basic requirement for surgeons to understand and analyze the fiber tracking results is to have an interactive 3D view in which a user can pan, rotate, and zoom. Furthermore, they need to manipulate the magnetic resonance T1-weighted slices to comprehend the relation to the anatomy. How users used those interactions was not part of the study and was not recorded to comply with data minimization goals of the host institutions' ethics guidelines for human studies.

Questionnaire setup

To fill in the questionnaire and be a part of this study, participants were first requested to provide digital consent, indicating their willingness to partake in the study. This initial step ensured that participants were fully aware of their involvement and agreed to the terms of the study. Its to be noted the participants were not asked for any Personal Identifiable Information (PII), such as name or email address. Once consent was obtained, the participants were asked for information about their experience with fiber tracking techniques, such as for how long they have been using fiber tracking results in their workflow. By obtaining this context, we aimed to gain insights into potential variations in the interpretation and utilization of the provided uncertainty visualization.

In the following step, participants were presented with a set of instructions that served to introduce them to the concepts of uncertainty visualization used in fiber tracking results and a description of the tasks they would undertake. These instructions were crucial in establishing a common understanding and setting the stage for the subsequent phases of the evaluation. Once the details are provided, participants are presented with the training page, depicted in Figure 5. This page served as a tangible introduction to the 3D interface participants would be utilizing throughout the evaluation process. The training page showcased the layout of the visualization and outline of how they could interact with the system, thereby allowing participants to become acquainted with the 3D interface and its features. In the training phase, participants were allowed to explore all the uncertainty intervals by selecting the corresponding icon. The participants can get familiar with the different uncertainty intervals as concepts

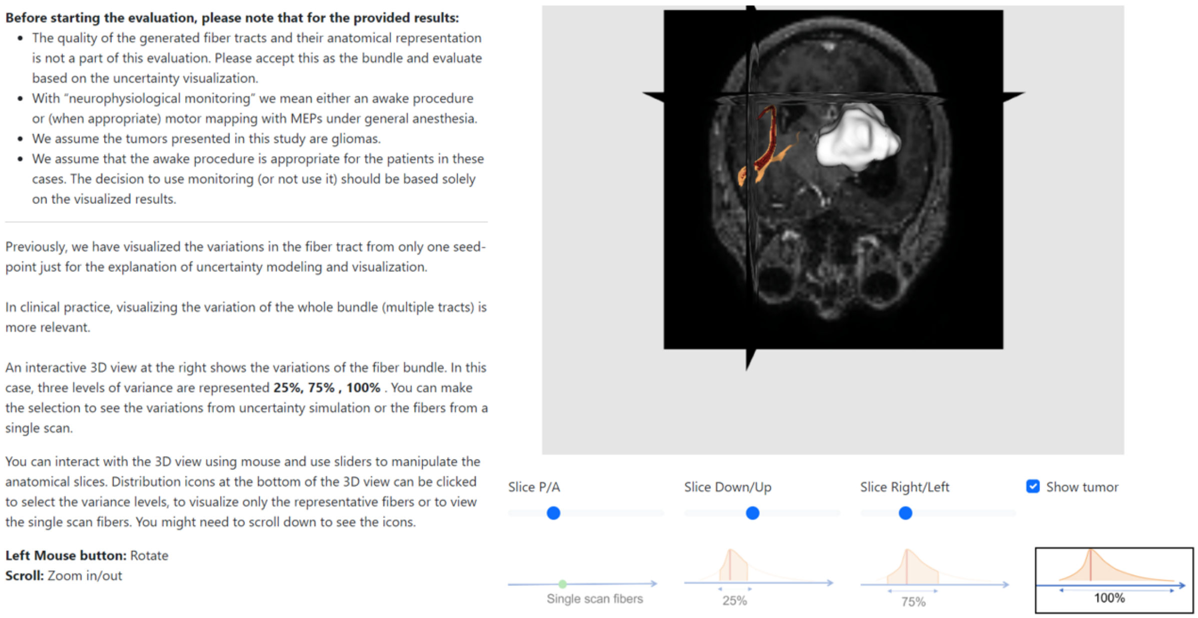

FIGURE 5. This screenshot captures the training page, delineating essential elements for the evaluation process. On the left side, detailed information regarding the assumptions made for the evaluation and instructions for utilizing the 3D interface is provided. The right side of the page features an interactive 3D interface seamlessly embedded, accompanied by controls located at the bottom for user interaction.

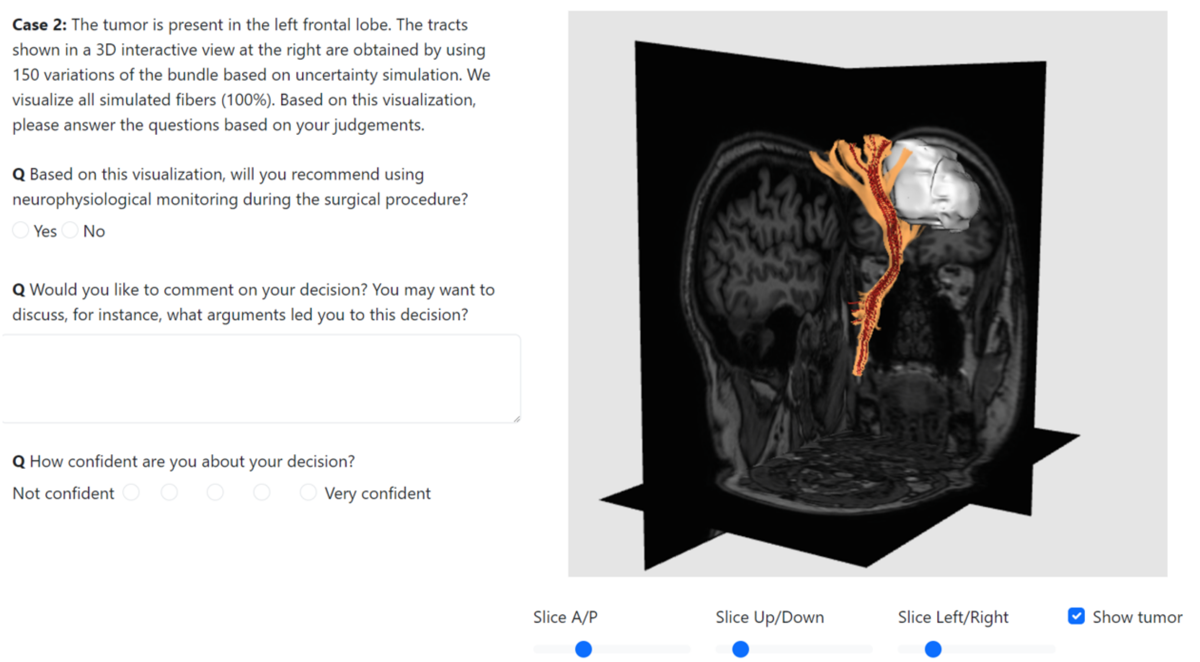

FIGURE 6. This screenshot encapsulates a specific case within the evaluation framework. On the left side, a set of questions related to the case is presented. Simultaneously, on the right side, an interactive 3D interface is integrated, facilitating a comprehensive exploration of the case, with user controls conveniently positioned at the bottom for enhanced interaction.

and the consequences of making specific selections. After the training phase, participants were asked to answer questions to check if their understanding of the uncertainty visualizations presented.

In total, each participant was presented with eight different cases as discussed above. Each case was presented using an interactive 3D view showcasing the fiber tracking results, anatomical context, and the tumor on its own page, together with the corresponding questions as shown in Figure 6. Responses from participants were collected through the selection radio buttons and the dialog box.

By visualizing the results with and without uncertainty information along with different intervals, we were able to test if participants were switching their decision to using IONM. This allowed us to determine how the inclusion of uncertainty information changed the participant's response (H1). By analyzing their decisions based on the interval of visualized uncertainties, we can determine if the participants are making more cautious decisions with higher intervals of uncertainty visualization (H2). The question on the confidence rating allows analysis of the influence of uncertainty visualization on participants' confidence (H3).

Following the participants' evaluation of all presented cases, we posed several open-ended questions concerning the uncertainty visualization in fiber tracking results. More precisely, we inquired whether the provided uncertainty information had any influence on any other clinical decisions beyond the application of IONM. Furthermore, we sought to determine whether the conveyed uncertainty information contributed to enhancing their decision-making confidence.

Results

The developed web application for the questionnaire was distributed among neurosurgeons throughout the Netherlands through the Dutch Association for Neurosurgery (De Nederlandse Vereniging voor Neurochirurgie). The association includes nearly all neurosurgeons practicing in the Netherlands. However, not all of these neurosurgeons perform brain tumor surgery, and only a portion of those who do use fiber tracking in their workflow. We received responses from 16 participants who were utilizing fiber tracking for their neurosurgical planning. Among these participants, one response was incomplete, leading us to base our analysis on the data from 15 complete responses. All the participants' responses to the training phase were 100 % correct, which indicates that the participants were able to understand the uncertainty interval visualization. To assess the potential impact of distinct uncertainty visualization intervals on participants' decisions (H1 and H2) and their corresponding confidence (H3), we utilized the responses to the provided questions for each case. We refrain from quantitative statistical analysis given the limited amount of samples. Therefore, we opt for a qualitative analysis.

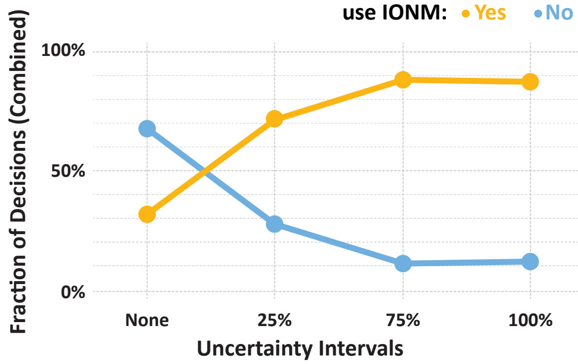

FIGURE 7. Overview of the trend of decisions taken by all participants (in percent) for the different uncertainty intervals.

Impact on decisions (H1 and H2)

We start our analysis by examining the choices made by participants in response to the question *"Will you recommend using Intraoperative Neurophysiological Monitoring (IONM) during the surgical procedure?"* across varying uncertainty interval visualizations. Figure 7 shows the percentage of decisions classified as **Yes**, use IONM, and **No**, do not use IONM, across the four different visualized uncertainty intervals. The results are summarized for all cases and participant responses. As can be observed in the plot, in the

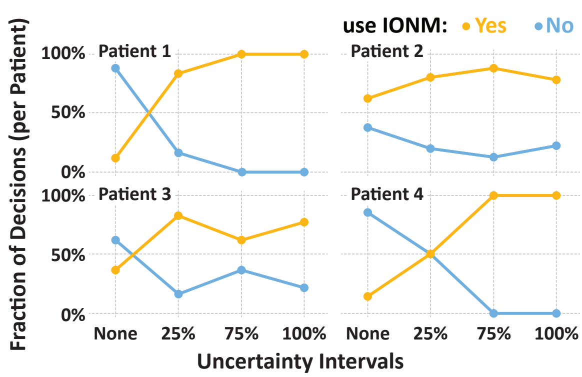

FIGURE 8. Combined result of the decision taken (in percent) versus uncertainty intervals per patient.

absence of uncertainty visualization (no uncertainty interval), a larger proportion of participants opted not to employ IONM for tumor resection procedures, and, therefore, taking a higher risk. However, as an uncertainty interval was visualized, an indication of a shift in the trend occurred, with participants displaying a greater inclination towards utilizing IONM, as depicted with the upward trend of the orange line in the plot, thereby supporting our hypothesis H1. This indicates that participants tend to adopt more conservative decisions when confronted with visualization of higher uncertainty intervals, providing support for hypothesis H2.

Figure 8 further divides the results into patient-specific trends to identify whether there were biases depending on the data sets (see Figure 3 as reference). The results depict the percentage of decisions classified of all participants for the four different patients. The results are similar to the overall results as shown in Figure 7. For Patient 1 and Patient 4, all participants opted for Yes for the 75% and 100% uncertainty interval visualizations. However, for Patient 2 and Patient 3, there is larger disagreement among participants. Independently of the visualized uncertainty interval, some participants chose No. This diversity in decisions can be attributed to the less clear margins of the tumor for Patients 2 and 3. The results indicate that uncertainty visualization impacts decision-making differently across different patients and participants.

For further analysis of the results, Figures 9 and 10 summarize the decisions and changes thereof for each participant individually. We want to account for participants intrinsic biases, for example, being prone to take more risks than others. We are interested in the changes in decision-making due to uncertainty visualization, not necessarily on the exact decision concerning IONM. Figure 9 depicts the count of the responses per participant for each uncertainty interval accumulating over the four presented patients (see *Study Design*).

Figure 10 presents the individual decisions as dots to highlight variation in the decisions per participant for different uncertainty intervals and per patient dataset. Therefore, the participant panels are further subdivided into four quadrants for the four patients (same order as Figure 8). The two dots corresponding to the two different uncertainty intervals for the same patient are connected to indicate change in decision. Green lines denote instances where the decision changed from No to Yes meaning changing to a less risky decision, while red lines signify the opposite, indicating a shift towards a more risky decision which is less expected. Grey lines indicate no

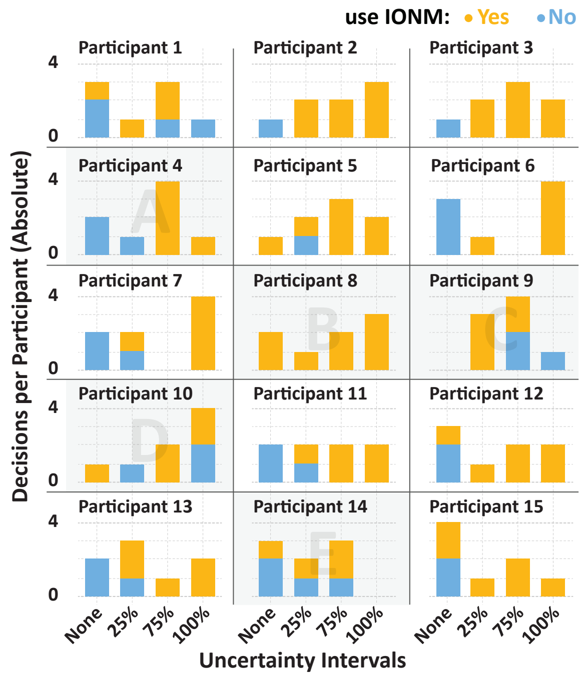

FIGURE 9. Count of the binary decisions versus uncertainty intervals for each participant.

change in the decision. Figure 9 underscores the general trend of participants shifting their decisions from No to Yes in response to larger uncertainty intervals visualized, consistent with earlier observations.

Overall, these results exhibit a consistent pattern similar to the previous results, where participants tend to favor the Yes decision when a larger uncertainty interval is visualized. No answers are mainly present when no or 25% of uncertainty is presented. Similarly, we observe in Figure 10 that most participants either did not change their decision ( ) or changed from No to Yes ( ) when larger uncertainty intervals were presented.

We will illustrate the results with some examples marked as **A** and **B**; and participants that behave differently than the main trend , marked **C** and **D**.

Let us first consider Participant 4 marked **A** in Figures 9 and 10. Participant 4 only makes the more conservative decision Yes once presented with uncertainty intervals of 75% and larger (see **A** in Figure 9). For Patient 1 (see top left corner in the panel marked **A** in Figure 10), Participant 4 was faced with no uncertainty and a 75% uncertainty interval. With no uncertainty presented, Participant 4 opted for No. However, when presented the 75% uncertainty interval of the same patient their decision changed to Yes. A similar effect can be seen in the answers of Participant 4 with the

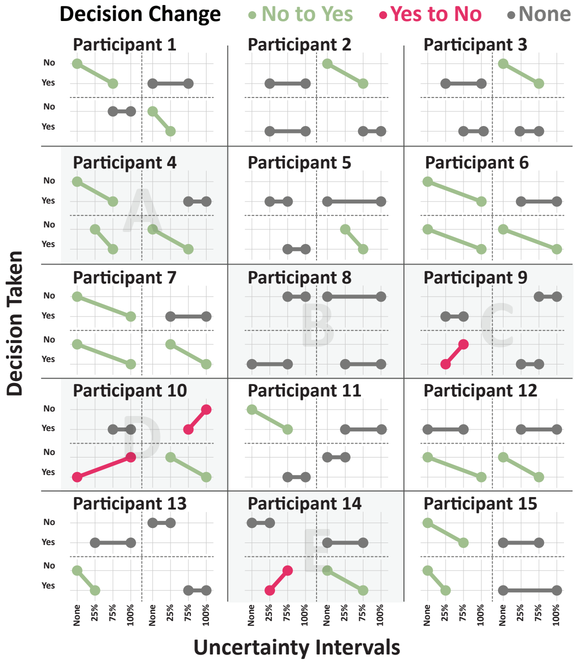

FIGURE 10. Change in participants' decision with uncertainty intervals. Dots represent the individual decision per participants for different uncertainty intervals and per patient dataset. The plots are further subdivided into four quadrants for the four patients. The dots are connected to indicate the change in decision.

other patients. Their responses align with the majority of participants.

Participant 8 (**B**) consistently selects **Yes** for all presented cases, regardless of the interval of uncertainty visualization or the patients involved. This would indicate that this participant favors minimal risk and it is more inclined to operate with IONM regardless.

The trend of either not changing the decision or changing towards a more conservative decision when presented with higher uncertainty intervals is present in the majority of the answers. However, Participants 9, 10, and 14 (**C**, **D**, and **E**, respectively) exhibit a distinct pattern concerning Patient 3 (i.e., bottom-left corner of the respective panels in Figure 10). They chose **No** for cases with high uncertainty interval visualization and **Yes** for low uncertainty intervals. It is unclear why these distinct choices were made by these participants. There might be some specifics of the Patient 3 data set that make this decision different. We also observe that Participant 10 (**D**) exhibits the same distinct pattern with Patient 2, although this is not observed in any other participant.

Impact on confidence (H3)

To test Hypothesis H3, we analyzed the relation between participants' confidence and the visualized uncertainty interval. Figure 11 displays the self-reported confidence per participant, case and uncertainty interval. Participants were requested to rate their decision confidence on a 5-point Likert scale. The results offer an overview of participants' confidence across different uncertainty scenarios. We can observe two main trends: participants have a rather constant confidence level that is not influenced by the presented uncertainty (i.e., Participants 1, 2, 3, 5, 10, 11, 12, 14, 15) or there is a slight correlation between confidence and intervals of uncertainty (i.e., Participants 4, 6, 7, 8, 13). Participant 9 (**C**) is the only participant that shows a negative correlation with the visualized uncertainty interval.

These results provide initial insights into how uncertainty visualization impacts confidence of participants in their decisions(H3). The visualized uncertainty intervals mostly seem to not influence the level of confidence, while for a few participants, they slightly correlate with the level of confidence positively.

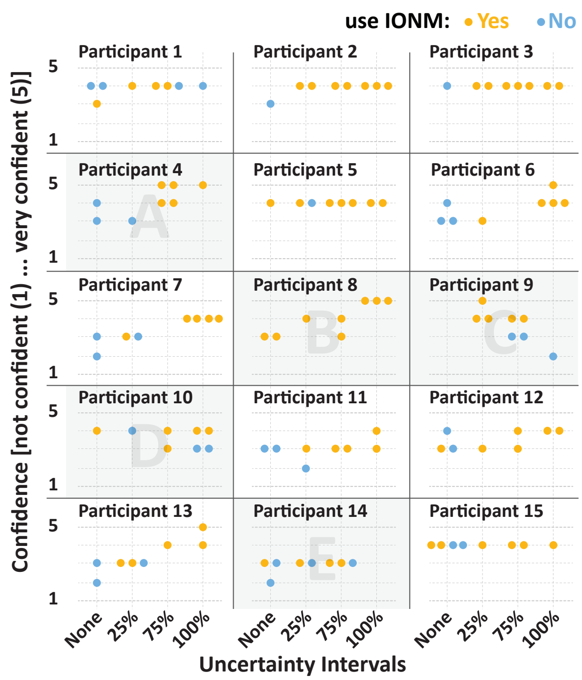

FIGURE 11. Overview of the participants' confidence across different uncertainty intervals visualizations and cases. Each point represents one of the eight cases that each participant addressed. The answer to the decision of using IONM is shown in orange for **Yes** and blue for **No**.

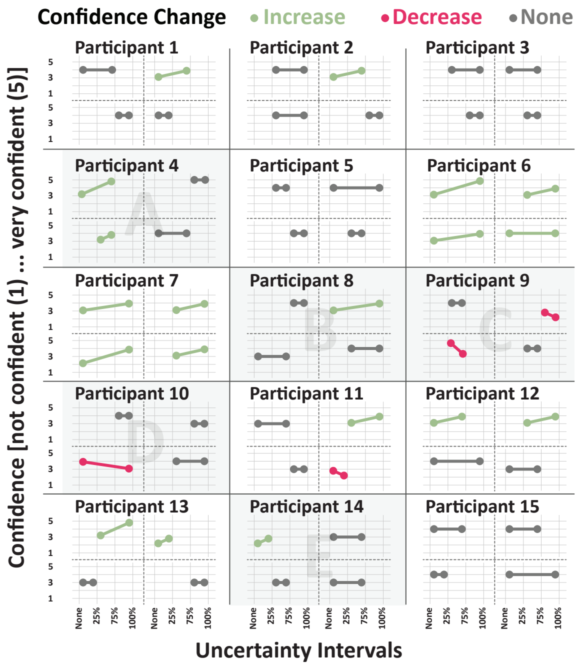

FIGURE 12. Change in participants' confidence with increasing uncertainty intervals. Dots represent the selected confidence per participant for different uncertainty intervals and per patient data-set. The plots are further subdivided into four quadrants for the four patients. The dots are connected to indicate the change in confidence.

Analogous to the previous section, we also want to examine whether the confidence of the participants changes with increasing uncertainty intervals. Figure 12 presents the changes in the confidence level of each participant for all four patients along with the uncertainty interval. Similar to above, green lines indicate increasing confidence while red lines represent decreasing confidence. Flat grey lines indicate no change in confidence. The chart reveals that the dominant trend is no change in confidence (38 cases), followed by increase in confidence (18 cases) and only four occurrences with a decrease in confidence. The confidence of Participants 9 and 10 (**C** and **D**, respectively) decreased, coinciding with the change of decision from Yes to No in Patient 3. These results confirm the results from Figure 11, although here we looked at the concrete change in confidence within the same decision context, i.e., patient.

Further information

We also compiled data regarding the years of professional experience of each participant to conduct an analysis of the relationship between their experience and decision-making processes. However, we did not identify any correlation between experience and the answers to the questionnaire and thus omit the data in this presentation.

Open-ended responses for each case were rather limited and focused mainly on clarifying the use of the distance from the tumor to the fiber tracts presented. A total of four participants responded to each open-ended question for all the cases, while others just responded once or twice. In total, we got 43 responses. Some examples being *"Too close, I would recommend using monitoring"*, *"In the results shown by DTI, the tracts are close proximity with edema and glioma"*, and *"there is enough space and window to remove the tumor."* These responses indicate that the decision making is highly dependent on the distance of the fibers to the tumor. However, the answers do not reveal any reasoning concerning uncertainty.

Discussion

The findings from this study indicate that participants incorporate the uncertainty information presented alongside the fiber tracking results into their decision-making process. When faced with visualizations showing higher uncertainty, participants tended to make more cautious judgments, as depicted in Figure 7 and Figure 8. Both analyses provided support for the hypotheses, largely aligning with the expected patterns which also align with the results of the study by Padilla[6]. Nevertheless, certain individual responses displayed distinct behaviors. For instance, Participant 8 (**B**) consistently favored employing IONM. It is difficult to speculate about what accounts for the lack of an impact of uncertainty visualization in the participant's decision. Participants 9, 10, and 14 (**C**, **D**, and **E**) opted for not using IONM when presented with higher uncertainty intervals for Patient 3. However, the confidence of Participants 9 and 10 (**C** and **D**) also decreased. Possible reasons might be participants ignoring the uncertainty information or making extremely cautious decisions. There might be some particular context of Patient 3 that contributed to these decisions. However, we could not identify any such cause. Furthermore Participant 9 (**C**) seems to have an overall different behaviour changing the decision making to a more risky situation, i.e., No IONM, when presented with higher intervals of uncertainty. Furthermore, the participant was the only one that showed a negative correlation of uncertainty with confidence. The participant might be an outlier on the decision-making process, or other factors had influence. Some of these factors could be misunderstanding what was presented or how uncertainty influenced the decision process was different than the rest of participants. However, within this study, we could not identify any such factors. Given the limited number of participants, a statistical analysis was not possible. However, the qualitative evaluation of the evidence shows the trends where uncertain information gives more cautious decisions.

It is important to acknowledge that numerous factors exert influence on neurosurgical decisions, including tumor type, or patient age. Despite our efforts to isolate uncertainty visualization from other variables and emphasize decision-making based on the provided visualization, it is not easy to judge that the decisions are purely based on the uncertainty visualization. Our conjecture was that presenting uncertainty information might impact participants' decisions. However, upon analyzing the limited open-ended responses, it indicates that those participants based their decisions on the proximity of resulting fiber tracts to the tumor. Consequently, our analysis suggests that while participants' decisions were influenced by provided uncertainty information, their focus predominantly might lay in assessing fiber tracking margins relative to the tumor and the number of fibers and potentially ignoring the statistical information of the uncertainty intervals of the fibers. Increasing uncertainty intervals also increases the total number of fibers shown. As a result more fibers closer to the tumor will be shown. However, we had very limited responses to our open questions, and our study was not designed to clarify the reasoning made by the participants when evaluating uncertainty. A full new study to evaluate this impact should be designed to make any conclusions.

Using a web-based questionnaire allows us to reach more participants, but at the same time, it discourages the answer to open-ended questions. These are essential to understand the reasoning aspects behind the decison-making of the participants. Exploring other user-study methods that include a stronger feedback loop could help increase responses to open-ended questions.

Lastly, our analysis delved into the influence of the presented uncertainty interval on the participants' confidence in their decision. Notably, the majority of responses indicate no change in confidence for different uncertainty intervals in the same patient, while an increase in confidence could be observed in a smaller amount of cases. A detailed examination of individual cases reveals a prevailing trend of either unaltered confidence or, for a few cases, a shift towards higher levels in scenarios with greater uncertainty. Our results are rather indecisive. A correlation is not evident, the findings indicate the partial influence of uncertainty for some participants. More extensive studies would be needed to achieve stronger statements.

Conclusions and Future Directions

For this study, we build upon the context and hypotheses established by Padilla et al.[6] to examine how uncertainty visualization affects decision-making when dealing with intricate fiber-tracking results in brain tumor patients. Collaborating with surgeons and radiologists, we designed and implemented a user study tailored to inquire about specific clinically relevant cases and analyze participants' decisions. Our investigation centered on exploring the impact of uncertainty visualization on neurosurgical decision-making through fiber tracking results. We carefully designed an interactive web-based questionnaire that allowed the participants to explore the necessary information to answer the decision-making questions. The evaluation, guided by the presented hypotheses, provides insights into the relationship between uncertainty presentation and participants' judgments. The findings underscore that uncertainty visualization influences participants' decisions, albeit its extent is also influenced by other factors.

As hypothesized, participants exhibited a tendency to make more cautious decisions when confronted with larger uncertainty intervals in the visualization. It should be noted, however, that the participants' decisions seem to be influenced by the number of fibers present, regardless of the statistical significance of the uncertainty interval visualization. In future studies, this should be explored to better understand the reasoning behind the decisions made.

Moreover, our analysis could not identify any clear relationship between the uncertainty intervals presented and participants' confidence in the decision-making. There is an indication of a positive correlation for some participants. Further studies are needed, to better understand the possible influence of uncertainty presentation on confidence.

Our analysis is constrained by several limitations. These limitations encompass a restricted number of users, limited data sets, limited questions, difficulty to acquire responses to open questions, and constraints related to the visualization itself. Further studies are needed such that these limitations can be overcome. In essence, this study contributes to our understanding of how uncertainty visualization intertwines with neurosurgical decision-making. The findings underscore the need to consider uncertainty information as a valuable component in the decision-making process, yet also highlight the complex nature of clinical judgments, which are shaped by a multitude of factors. Future research could delve deeper into understanding participants' decision strategies and their ability to grasp and use the concept of uncertainty. Furthermore, the influence of the specific visualization technique in the decision-making process was out of the scope of our work, but would also be of interest for future work.

Ethics Statement

The studies involving human participants were reviewed and approved by the Delft University of Technology Human Research Ethics Committee (HREC). The participants provided their digital informed consent to participate in this study.

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REFERENCES

1. J. Hullman, "Why authors don't visualize uncertainty," *IEEE Transactions on Visualization and Computer Graphics*, vol. 26, no. 1, pp. 130–139, 2019. DOI: 10.1109/TVCG.2019.2934287.
2. S. Mori, B. J. Crain, and P. C. Van Zijl, "3D brain fiber reconstruction from diffusion MRI," *NeuroImage*, vol. 7, no. 4 PART II, S710, 1998. DOI: 10.1016/S1053-8119(18)31543-X.
3. F. Henderson, K. G. Abdullah, R. Verma, and S. Brem, "Tractography and the connectome in neurosurgical treatment of gliomas: The premise, the progress, and the potential," *Neurosurgical Focus*, vol. 48, no. 2, E6, 2020. DOI: 10.3171/2019.11.FOCUS19785.
4. T. Schultz, A. Vilanova, R. Brecheisen, and G. Kindlmann, "Fuzzy fibers: Uncertainty in dMRI tractography," *Scientific Visualization: Uncertainty, Multifield, Biomedical, and Scalable Visualization*, pp. 79–92, 2014. DOI: 10.1007/978-1-4471-6497-5_8.
5. T. Schultz and A. Vilanova, "Diffusion MRI visualization," *NMR in Biomedicine*, e3902–n/a, Jan. 2018. DOI: 10.1002/nbm.3902.
6. L. M. Padilla, M. Powell, M. Kay, and J. Hullman, "Uncertain about uncertainty: How qualitative expressions of forecaster confidence impact decision-making with uncertainty visualizations," *Frontiers in Psychology*, vol. 11, p. 579 267, 2021. DOI: 10.3389/fpsyg.2020.579267.
7. F. Siddiqui, T. Höllt, and A. Vilanova, "A progressive approach for uncertainty visualization in diffusion tensor imaging," in *Computer Graphics Forum*, Wiley Online Library, vol. 40, 2021, pp. 411–422. DOI: 10.1111/cgf.14317.
8. G.-J. M. Rutten *et al.*, "Executive functional deficits during electrical stimulation of the right frontal aslant tract," *Brain Imaging and Behavior*, vol. 15, no. 5, pp. 2731–2735, 2021. DOI: 10.1007/s11682-020-00439-8.
9. P. D. W. Hamer, S. G. Robles, A. H. Zwinderman, H. Duffau, M. S. Berger, *et al.*, "Impact of intraoperative stimulation brain mapping on glioma surgery outcome: A meta-analysis," *J Clin Oncol*, vol. 30, no. 20, pp. 2559–2565, 2012. DOI: 10.1200/JCO.2011.38.4818.
10. H. Griethe and H. Schumann, "Visualizing uncertainty for improved decision making," in *Proceedings of International Conference on Perspectives in Business Informatics Research*, vol. 20, 2005.
11. A. T. Pang, C. M. Wittenbrink, S. K. Lodha, *et al.*, "Approaches to uncertainty visualization," *The Visual Computer*, vol. 13, no. 8, pp. 370–390, 1997. DOI: 10.1007/s003710050111.
12. H. Griethe and H. Schumann, "The visualization of uncertain data: Methods and problems," in *Proceedings of SimVis*, 2006.
13. M. Skeels, B. Lee, G. Smith, and G. G. Robertson, "Revealing uncertainty for information visualization," *Information Visualization*, vol. 9, no. 1, pp. 70–81, 2010. DOI: 10.1145/1385569.1385637.
14. F. Siddiqui, T. Höllt, and A. Vilanova, "Uncertainty in the DTI visualization pipeline," in *Anisotropy Across Fields and Scales*, Springer, Cham, 2021, pp. 125–148. DOI: 10.1007/978-3-030-56215-1_6.
15. M. Mirzargar, R. T. Whitaker, and R. M. Kirby, "Curve boxplot: Generalization of boxplot for ensembles of curves," *IEEE Transactions on Visualization and Computer Graphics*, vol. 20, no. 12, pp. 2654–2663, 2014. DOI: 10.1109/TVCG.2014.2346455.
16. F. Enders *et al.*, "Visualization of white matter tracts with wrapped streamlines," in *Proceedings of IEEE Visualization*, IEEE, 2005, pp. 51–58. DOI: 10.1109/visual.2005.1532777.

17. R. Brecheisen, B. Platel, B. M. ter Haar Romeny, and A. Vilanova, “Illustrative uncertainty visualization of DTI fiber pathways,” *The Visual Computer*, vol. 29, no. 4, pp. 297–309, 2013. DOI: 10.1007/s00371-012-0733-9.
18. E. Dimara and J. Stasko, “A critical reflection on visualization research: Where do decision making tasks hide?” *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 1, pp. 1128–1138, Jan. 2022. DOI: 10.1109/tvcg.2021.3114813.
19. S. Deitrick and R. Edsall, “The influence of uncertainty visualization on decision making: An empirical evaluation,” in *Proceedings of International Symposium on Spatial Data Handling*, Springer, 2006, pp. 719–738. DOI: 10.1007/3-540-35589-8_45.
20. L. M. Padilla, S. H. Creem-Regehr, M. Hegarty, and J. K. Stefanucci, “Decision making with visualizations: A cognitive framework across disciplines,” *Cognitive research: principles and implications*, vol. 3, no. 1, pp. 1–25, 2018. DOI: 10.1186/s41235-018-0120-9.
21. M. S. Roulston, G. E. Bolton, A. N. Kleit, and A. L. Sears-Collins, “A laboratory study of the benefits of including uncertainty information in weather forecasts,” *Weather and Forecasting*, vol. 21, no. 1, pp. 116–122, 2006. DOI: 10.1175/WAF887.1.
22. S. L. Joslyn and J. E. LeClerc, “Uncertainty forecasts improve weather-related decisions and attenuate the effects of forecast error.,” *Journal of experimental psychology: applied*, vol. 18, no. 1, p. 126, 2012. DOI: 10.1037/a0025185.
23. M. S. Roulston and T. R. Kaplan, “A laboratory-based study of understanding of uncertainty in 5-day site-specific temperature forecasts,” *Meteorological Applications: A journal of forecasting, practical applications, training techniques and modelling*, vol. 16, no. 2, pp. 237–244, 2009. DOI: 10.1002/met.113.
24. M. H. Ramos, S. J. Van Andel, and F. Pappenberger, “Do probabilistic forecasts lead to better decisions?” *Hydrology and Earth System Sciences*, vol. 17, no. 6, pp. 2219–2232, 2013. DOI: 10.5194/hess-17-2219-2013.
25. M. Korporaal, I. T. Ruginski, and S. I. Fabrikant, “Effects of uncertainty visualization on map-based decision making under time pressure,” *Frontiers in Computer Science*, vol. 2, p. 32, 2020. DOI: 10.3389/fcomp.2020.00032.
26. C. Gillmann, D. Saur, T. Wischgoll, and G. Scheuermann, “Uncertainty-aware visualization in medical imaging-a survey,” in *Computer Graphics Forum*, Wiley Online Library, vol. 40, 2021, pp. 665–689. DOI: 10.1111/cgf.14333.
27. M. Galesic, R. Garcia-Retamero, and G. Gigerenzer, “Using icon arrays to communicate medical risks: Overcoming low numeracy.,” *Health psychology*, vol. 28, no. 2, p. 210, 2009. DOI: 10.1037/a0014474.
28. M. McDowell and A. Kause, “Communicating uncertainties about the effects of medical interventions using different display formats,” *Risk Analysis*, vol. 41, no. 12, pp. 2220–2239, 2021. DOI: 10.1111/risa.13739.
29. J. Hullman, X. Qiao, M. Correll, A. Kale, and M. Kay, “In pursuit of error: A survey of uncertainty visualization evaluation,” *IEEE Transactions on Visualization and Computer Graphics*, vol. 25, no. 1, pp. 903–913, 2018. DOI: 10.1109/TVCG.2018.2864889.
30. S. Mori, B. J. Crain, V. P. Chacko, and P. C. Van Zijl, “Three-dimensional tracking of axonal projections in the brain by magnetic resonance imaging,” *Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society*, vol. 45, no. 2, pp. 265–269, 1999. DOI: 10.1002/1531-8249(199902)45:2%3C265::AID-ANA21%3E3.0.CO;2-3.
31. W. Schroeder, K. M. Martin, and W. E. Lorensen, *The visualization toolkit an object-oriented approach to 3D graphics*. Prentice-Hall, Inc., 1998.

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