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Visually communicating pathological changes: A case study on the effectiveness of phong versus outline shading

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ABSTRACT

In this paper, we investigate the suitability of different visual representations of pathological growth and shrinkage using surface models of intracranial aneurysms and liver tumors. By presenting complex medical information in a visually accessible manner, audiences can better understand and comprehend the progression of pathological structures. Previous work in medical visualization provides an extensive design space for visualizing medical image data. However, determining which visualization techniques are appropriate for a general audience has not been thoroughly investigated.

We conducted a user study (n = 40) to evaluate different visual representations in terms of their suitability for solving tasks and their aesthetics. We created surface models representing the evolution of pathological structures over multiple discrete time steps and visualized them using illumination-based and illustrative techniques. Our results indicate that users' aesthetic preferences largely coincide with their preferred visualization technique for task-solving purposes. In general, the illumination-based technique has been preferred to the illustrative technique, but the latter offers great potential for increasing the accessibility of visualizations to users with color vision deficiencies.

1. Introduction

Various pathological conditions change over time, often showing growth within the human body while treatment might lead to shrinkage. Understanding and communicating these temporal changes to an audience with potentially limited health literacy is challenging. However, since the growth of pathological structures is essential for treatment planning and outcome predictions, communicating it to a general audience facilitates informed consent as a patient and can be used to promote prevention, such as regular screening for certain diseases. In this context, narrative medical visualization, with its focus on engaging, memorable, and comprehensible visualizations enriched with textual information, is promising to communicate medical data [1]. By combining appropriate data visualization and interaction techniques with storytelling elements, medical professionals and educators can empower non-experts to understand complex medical data, facilitating informed decision-making, health literacy, and patient engagement.

Visualization techniques that emphasize the temporal dimension can help illustrate the progression of pathological conditions over time. Interactive features such as annotations, navigation buttons, or rotatable objects allow viewers to explore the data at their own pace and focus on specific details of interest. However, they need to be carefully designed to be feasible for a broad audience. In this study, we build on our previous work, where we compared three different visualization styles and explored user preference for displaying multiple time steps side-by-side or sequentially, similar to an animation [2]. Based on feedback from our clinical partners and the results of the previous study, we are diving into a detailed analysis of the difference between illumination-based and illustrative visualization techniques, as well as both growth and shrinkage. We noticed that rotation, although extremely useful for studying morphological changes of 3D visualizations of pathologies, was rarely used by the participants. Therefore, this work is specifically dedicated to ensuring a consistent use of rotation by implementing it using buttons, since they are well-known UI elements. Tracking their use enables us to investigate how interaction and user performance in solving tasks are related. We use surface models of intracranial aneurysms and liver tumors to represent their evolution over discrete time steps. The models were rendered using two techniques, namely Phong and outlines. We chose aneurysms and liver tumors because they are representative of cancer and vessel diagnosis, two essential medical problems. While tumors often grow in all dimensions,

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aneurysms tend to have a more distinct direction of growth. In a user study with 40 participants with varying medical expertise, we compared our visualizations in terms of their ability to assess growth processes and their aesthetics.

This paper makes valuable contributions to the field of medical visualization by conducting an exploratory case study that evaluates well-established techniques with a diverse audience, encompassing varying levels of health literacy. It provides insights into the convergence and divergence of visual preferences among non-expert users and their performance in solving tasks using different visualization styles. By exploring the feasibility of visualizations to effectively convey growth and shrinkage in medical image data, the paper offers practical recommendations for conveying complex medical concepts to a broader audience. The findings and discussions presented in this paper serve as a foundation for enhancing the design and implementation of medical visualizations, ensuring they are accessible, engaging, and informative for a general audience.

2. Related work

In this section, we discuss research on narrative visualization and its application to medical data communication, as well as visualization of temporal changes. These studies highlight the gaps that the current study aims to address.

2.1. Previous studies on narrative medical visualization

Several studies have examined the use of narrative visualization techniques in various domains, including healthcare and medical communication. The majority of this research has focused on information visualization [3,4]. Höhne [5] presented a first approach for interactive analysis of CT data by the general public in the context of a museum exhibition. Wohlfahrt and Hauser [6] designed an authoring tool for generating medical data-driven stories to increase the comprehensiveness when presenting medical volume data. Garrison et al. [7] investigated the preferences of experts and non-experts regarding the visualization of biomedical processes. Their results show that preferences depend on the level of expertise of the target audience. Users without domain expertise particularly disliked distracting or excessive visualizations. However, neither experts nor non-experts preferred extreme realism or extreme abstraction. Both groups valued visualizations that met the stated communication objective. For our target audience of non-experts, we use semi-realistic and illustrative visualizations. In contrast to Garrison et al. we focus on a specific communication objective and thus use tasks to test whether the user preferences match their performance in solving the tasks with a given visualization technique.

Meuschke et al. [1] conducted a study on how narrative visualization can be used to communicate disease data to non-experts, highlighting the improved comprehension and engagement of participants compared to traditional data presentation methods. Aesthetic aspects, such as an attractive and consistent design, play a crucial role. Similarly, Kleinau et al. [8] and Mittenentzwei et al. [9] explored the influence of using the narrative genres *slideshow* and *scrollytelling* for disease communication on usability and aesthetics. Bruza et al. [10] present an approach that uses a VR environment to enable domain experts, such as physicians, to create educational videos with 3D data. Mittenentzwei et al. [11] explored the impact of distinct human protagonists, including a patient and a physician, on users' trust, identification, and engagement with a narrative medical visualization. These manuscripts focus primarily on how to build and structure a data-driven story but do not explore which visualization techniques are appropriate for presenting medical data to a general audience.

2.2. Medical visualization for surface models

There are various options to visualize surface models of anatomical and pathological structures. Smoothing surface models to compensate for staircase artifacts resulting from the limited spatial resolution and the anisotropic character of medical image data is an essential prerequisite. Simple mesh smoothing approaches, however, lead to the loss of details and volume. Bade et al. [12] conducted a comparative study to assess the effectiveness of various mesh smoothing approaches in preserving anatomical shape features, using a tumor as an example. One essential smoothing method restricts the displacement of vertices to one diagonal of a voxel [13]. Moench et al. [14] minimized the negative effects of smoothing even further by restricting the displacement of vertices to those heavily affected by the anisotropic resolution. Their method was primarily used to smooth tumor models and present them in their surroundings. Later, Wei et al. [15] presented methods to better preserve the shape features of anatomical structures. The most recent methods towards this goal are based on deep learning [16]. Smoothing is particularly important for illustrative surface visualizations since these emphasize discontinuities of surface models. It would be misleading if these discontinuities represent artifacts instead of shape features. For vascular structures, special techniques were developed based on implicit surfaces aiming at a comprehensible rendering of their branching patterns [17].

Illumination-based techniques, like Phong, mimic the physical effects of light and create depth cues by adding highlights and shadows depending on a present light source. Thus, more realistic visualizations can be created. Phong shading is a basic shading technique, often used for comparative evaluations of state-of-the-art methods [18].

Illustrative rendering techniques are inspired by scientific illustrations and can be used to simplify visual representations through abstraction [19]. Essential illustrative rendering techniques are silhouette rendering, rendering of other feature lines, stippling, and hatching. Illustrative rendering can be integrated into direct volume rendering [20,21] or in surface rendering, which is more essential for this paper since we display surfaces of segmented anatomical and pathological structures. The realization of silhouette rendering and its integration with surface rendering was described by Tietjen et al. [22] and employed for visualizing tumors within the liver. Various visualization techniques can be categorized as silhouettes, contours, feature lines, stippling, hatching, and shading [23].

2.3. Visualization for longitudinal medical image data

Researchers have developed a range of techniques to capture and communicate changes over time in the field of visual analytics [24]. Zhang et al. [25] apply these techniques to the healthcare domain and highlight the importance of linked views. Accordingly, we have linked our visualizations of the different time steps, so that the rotation of one surface model is followed by the same rotation of all other surface models.

Visualizing longitudinal medical image data supports clinicians in the assessment of treatment response and patient prognosis. To enhance a visual comparison of different time steps, registration of the data sets is necessary. However, registration remains a challenging task, even using advanced deep learning techniques [26]. Sugathan et al. [27] visualized longitudinal brain lesion evolution of patients with multiple sclerosis. They focused on visualizing the lesions using contours and meshes. They showed the different time steps side-by-side and in an overlay view. We followed a similar approach by visualizing time steps side-by-side.

In contrast to studies that use longitudinal image data, tumor growth models provide a way to mathematically model the expected evolution of a tumor [28,29]. A similar approach has been investigated for aneurysms [30]. The predictions are used for treatment planning and prognosis.

3. Medical data sets

We chose intracranial aneurysms and liver tumors as examples of growth and shrinkage. The first disease is an example of a vascular

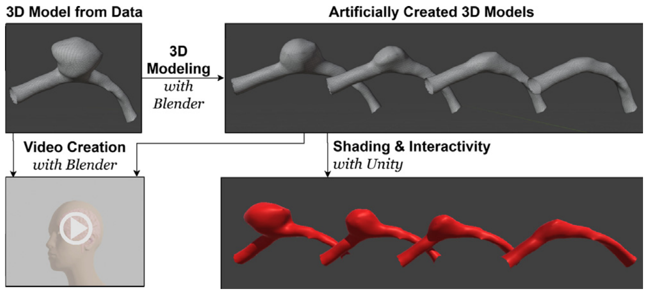

Fig. 1. Generation of the 3D models and visualizations. Based on the original 3D model of a pathology that was derived from data, we created additional time steps by step-wise shrinking the original model using Blender. One model per pathology that was not included in the tasks was used to create a short explanatory video about the pathology. Shading and interaction opportunities were added in Unity.

disease and the second disease represents tumor diseases, including cancer. About 3% of the adult general population is affected by saccular unruptured intracranial aneurysms [31]. Liver cancer is the fifth most common cancer and is responsible for 8.2% of cancer deaths worldwide [32].

Intracranial aneurysms are local dilations of blood vessels in the brain. They rarely cause symptoms but are at risk of rupturing and causing life-threatening intracranial hemorrhage. Aneurysms can grow and change shape over time, which is often considered a sign of increased risk of rupture [33]. Because treatment of aneurysms carries its risks, including rupture, many aneurysms that are considered stable (no enlargement >0.5 mm for at least 9 months) are not treated. However, it is important to monitor aneurysms to assess the risk of rupture, as even stable aneurysms can become unstable [34].

Unfortunately, there are few long-term data sets on the natural history of aneurysms. Many patients opt for treatment or do not return to the same hospital for regular follow-up. Since we did not have longitudinal data from multiple patients, we created artificial time steps, see Fig. 1. The volume of the original pathology was reduced by approximately the same factor in each artificially created time step. Therefore, we used surface models derived from real medical image data and shrunk them using the 3D modeling software *Blender* which can calculate the volume of a given 3D model. Thus, we also avoid the challenging registration problems that would occur if we would employ medical image data. In this way, we created up to five different alternations of each model showing how it might have looked as it grew.

As a second example, we focus on liver tumors. Like aneurysms, liver tumors rarely cause symptoms. In advanced stages, liver cancer can cause symptoms like weight loss, a loss of appetite, and pain [35]. For tumors, either curative or palliative treatment is provided soon after initial diagnosis [36]. Similar to the approach taken with the aneurysm data, we have artificially generated the time steps between a healthy liver and the initial tumor dataset by progressively shrinking the tumor size to create four distinct time steps.

We used three data sets of intracranial aneurysms and three data sets of liver tumors. The artificially generated time steps do not accurately reflect the actual changes in the structures over time. The primary goal is to educate a lay audience about general concepts, thereby mitigating the strict need for absolute accuracy. We discussed our artificial models with a senior physician in the neurology department and with the head of the radiology department. They agreed that our generated time steps are sufficient for educating an audience without expert medical knowledge as the growth patterns of pathologies can vary strongly for individual patients and our models depict plausible examples of growth patterns. In addition, when communicating medical concepts to lay audiences, simplifications are often used to make the topics more understandable. This is also highlighted by Drucker et al. [37] who argue that there needs to be a balance between the correctness of data visualization and addressing the literacy level of the audience. Nevertheless, we advocate the use of authentic data whenever possible. The creation of synthetic time steps is a resource-intensive process that requires the expertise of both a visualization specialist to create the 3D models and a medical expert to assess the credibility of the artificial data before it is suitable for medical briefings. The more complex the surface, the more this applies. Both aneurysms and tumors can develop bulges called blebs. Malignant tumors often have complex growth patterns with more growth near blood vessels, which is difficult to model artificially. Furthermore, empowering lay audiences to interpret real data addresses the increasing demand for evidence and credibility of presented information [38]. Although we resorted to additional artificial time steps due to the lack of real data, the results of our study are also relevant for similar real data sets.

4. Extensions to the prior study

This study serves as an extension of our previous research [2]. This section highlights the modifications made in the previous study's design. The current study design is described in detail in Section 5. Whereas the previous study centered on tasks involving data analysis and subsequent measurement of results, this aspect comprises only half of our current investigation. Specifically, participants are tasked with estimating whether the growth or shrinkage of pathologies follows a linear or non-linear trajectory, along with quantifying the volume changes between successive time steps. A consultation with our medical collaborators underscored the significance of communicating growth rates effectively to lay audiences. The remaining half of the evaluation is dedicated to soliciting participants' self-reported feedback on the visualization methods through the use of keywords, thereby providing further insights into their perceptions of the employed visualization techniques, which were not part of the prior study.

We included short videos explaining the pathologies to help the users better understand the application examples they are working with and increase motivation by highlighting the medical application. In contrast to the previous study, which showed five time steps, we decided to showcase only four time steps in this study. Presenting only four models side-by-side facilitates larger representations without overlap. The models that were removed from the tasks are shown in the explanatory videos. For growth, this refers to the healthy structure before the pathology develops, while for shrinkage, the videos include the fully grown pathology. Thus, the videos always show the initial anatomy before a growth or shrinkage process begins.

We elected to compare two shaders instead of three, eliminating the hatching shader employed in the previous iteration. By doing so we focus our current evaluation on the comparison of an illumination-based shading and an illustrative shader to facilitate a more detailed comparison between those. On the other hand, the third visualization in our last study was a combination of two techniques, namely hatching lines and Fresnel shader, making it difficult to analyze whether the results for this visualization were more influenced by one of the combined techniques. In addition, we chose to display the models side-by-side only, whereas, in the previous study, we compared a side-by-side view with a user-driven sequential view, where only one time step was displayed at a time. This decision makes the study more concise and allows for a more detailed comparison between the two shaders because, unlike our previous study, we can show multiple shaders to each participant. We wanted to keep the study small because each shader or presentation variant included would significantly increase the length of the study, making it more difficult to recruit participants and prevent them from dropping out during the study. Additionally, with increasing study duration, the concentration of participants decreases. Thus, this is a trade-off between the amount of content and the quality of results. Therefore, as we added new aspects to our study, we decided to remove one of the visualization techniques and the user-steered successive presentation variant.

Because we found in our previous study that many participants did not use the rotation, we implemented this interaction technique differently for this study. Rotation is still possible around one axis. While in the last study, participants could rotate the models by clicking and dragging their mouse in the 3D scene, we now use buttons for rotation. Buttons are an easy-to-use interface element that is widely used in many applications and, therefore, familiar to most people. Two buttons are displayed, one on each side of the screen to facilitate rotation to the left or right direction. The buttons display curved arrows, a typical representation of rotation, as additional cues to make them more intuitive to use.

5. Study design

The design space for visualizing changes in medical data sets is vast and we do not intend to cover it comprehensively with our study. Rather, we wanted to do an initial exploration of different style directions, namely illumination-based and illustrative methods, to get a direction for future design studies. We chose illumination-based shading because it is a classic, widely used, and easy-to-understand approach to visualizing 3D data [39]. On the other hand, illustrative techniques mimic pencil sketches, a style familiar even to lay people [7,23]. We chose Phong shading as an example of shading and outlines as an example of boundary emphasis. We decided to enhance the outlines with view-dependent feature lines to visualize the surfaces' ridges and valleys. The study design was significantly influenced by the two physicians mentioned in Section 3. According to them, aneurysms and tumors grow heterogeneously and there are many unanswered questions in medicine, especially in the treatment of aneurysms. However, these aspects are not particularly relevant when informing the general public. On the other hand, the aspects of growth rate and also the size ratios from one time step to another are important to understand the growth process. A high growth rate conveys the aggressiveness of the pathology. However, the pathologies must always be seen in their anatomical context to convey a coherent overall picture. It is also important to explain shrinkage processes. These can convey a more positive image and can explain and motivate treatments such as chemotherapy. Based on the physicians' comments, the following aspects were included in the study:

- Tumor and aneurysm growth and shrinkage are considered (treatment methods are briefly explained to motivate shrinkage).
- The tasks of the study include the perception of growth rate and size ratios.
- Anatomical context is presented.

5.1. Implementation of the visualizations

We implemented our visualizations in Unity 2021.3.7f1. Unity provides many prebuilt interaction techniques and shaders to help programmers efficiently implement interactive visualizations. Unity's built-in visual scripting for shader implementation, the Shader Graph, allows for the quick creation of simple shaders such as Phong and Fresnel shaders. Materials can be easily generated from shader files and applied to 3D meshes in the scene. Parameters, such as color or brightness of the material, can be adapted in the visual inspector or on run time. Unity's interface allows meshes to be arranged in a hierarchy where transformations applied to a parent automatically affect all of its children. Furthermore, Unity provides pre-built UI elements, such as drop-down menus and toggle buttons. This enables to quickly build an interactive three-dimensional scene using the visual editor. Videos explaining the anatomical context were also included in the study. The animations were created and recorded in Blender 4.0.

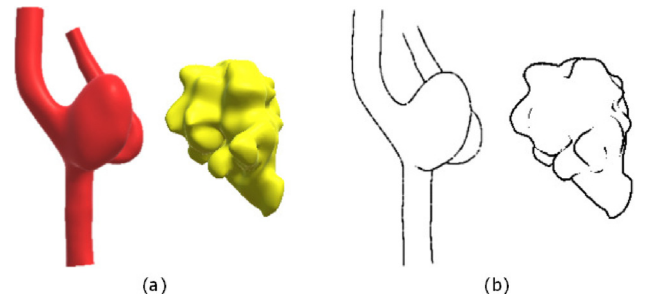

Fig. 2. Different visualization techniques for the aneurysm and tumor surface models. (a) shows Phong shading, (b) inverted hull outlines.

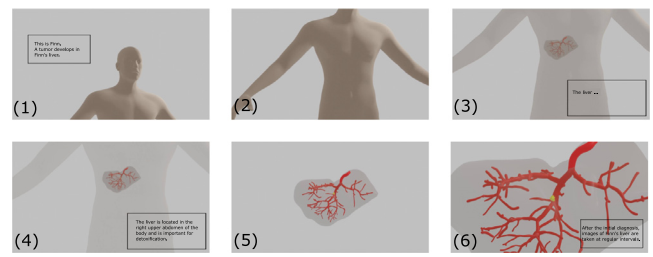

Fig. 3. Sample frames from a video explaining that the fictional character Finn developed liver tumors. For the (1) character introduction, the camera focuses on the head while (2) moving down and (3–6) gradually zooming in on the liver to show the tumor without losing the anatomical context. Text boxes introduce the character, the disease, and the organ affected by the disease.

5.2. Presentation of time steps

For each dataset, we created five time steps. In our evaluation, we have chosen to present four of these time steps side-by-side for the tasks. The fifth time step is used in an introductory video of the pathology, see Fig. 3. The videos contain a mini-story introducing a character with a corresponding pathology. A 3D model of a human is utilized, progressively zooming in until the pathology becomes visible. Each transition and pause lasts from two to seven seconds, varying with the complexity of the structure in view and whether text is being displayed. To illustrate growth, the first time step showcases the healthy structure. Conversely, to demonstrate shrinkage, we begin with the final time step, which represents the fully developed aneurysm or tumor.

For the tasks, on the one hand, we considered differentiating fewer time steps to be too simple, and on the other hand, adding additional time steps would increase the participant's processing time due to the additional time spent on analyzing all given time steps. We considered four steps to be a good balance between task complexity and a participant's processing time. In addition, the more time steps we displayed, the smaller each model had to be scaled because they were all displayed side-by-side on the screen. Four models can still be displayed at a reasonable size. The data sets are visualized using different shaders as described in the following sections.

5.3. Illumination-based visualization

We opted for an illumination-based representation of the surface models using a Phong shader to add highlights and shadows providing a semi-realistic appearance, see Fig. 2(a). We chose red for the aneurysm data sets because it is an intuitive color for an artery. We colored the tumors yellow to provide a good contrast to the surrounding vascular tree and liver tissue, which are colored in shades of red. Using a simplified, semi-realistic representation of the anatomical structures, our goal was to make the visualization more accessible to non-experts. While

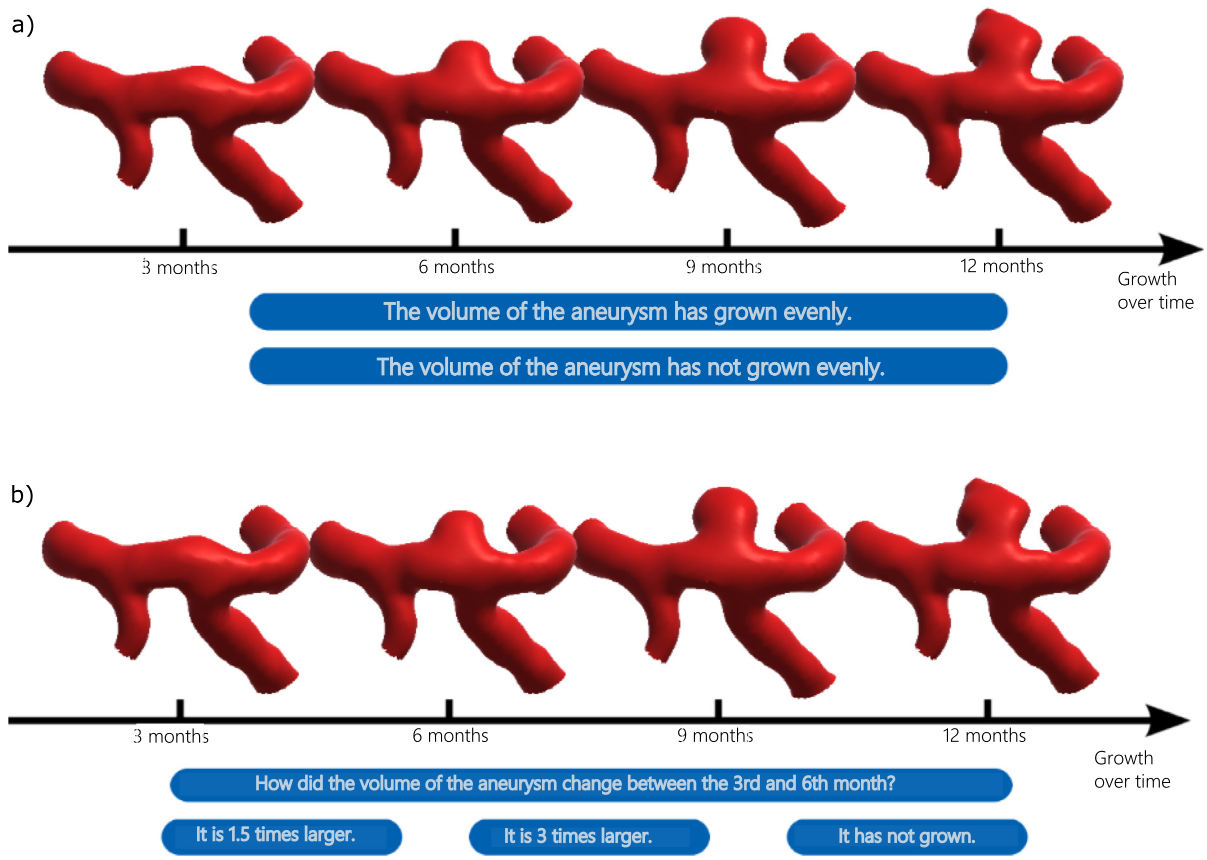

Fig. 4. First task of our user study. (a) Participants should assess whether (a) the overall growth changes linearly (evenly) or nonlinear (unevenly) and (b) how much the pathology has grown or shrunk for each pair of consecutive time steps.

realistic medical footage is often considered gross by many non-experts, our simplified models depict anatomical structures using conventional colors without being disturbing. We also follow the findings of Garrison et al. [7] who found that lay audiences particularly dislike distracting or excessive visualizations.

5.4. Illustrative visualization

We also implemented a stylized illustrative visualization, see Fig. 2(b). We used an outline shader that follows the principle of an inverse hull shader, where the object is rendered using a multi-pass approach [40]. In the first pass, the object is rendered with an unlit white shader. Then the outline is created in the second pass by scaling the object up slightly (we used the scaling factor of the object divided by 0.7) and rendering only the backside of the larger model in black. The result is an illustrative visualization reminiscent of a simple pencil drawing.

6. Evaluation

To evaluate the visualization techniques, we conducted a between-subjects design study. We set up an online study in which each user completed four tasks for the aneurysm datasets and four tasks for the tumor datasets. For each data set, users were required to complete tasks and indicate how confident they were in their answers. The study ran for about one month.

We created four evaluation sequences by presenting the visualizations to study participants in different orders to minimize bias. The same visualization techniques are always shown in two sequences but in different order. Each participant saw only one of the following sequences, which can be found online:

1.1 Phong starting with growth
1.2 Phong starting with shrinkage
2.1 Outline starting with growth
2.2 Outline starting with shrinkage

Each sequence was evaluated by ten participants. Therefore, each visualization technique was evaluated by 20 participants. We were careful to avoid our results being falsified by a learning effect or by pairing easier or more complex data sets with a certain visualization technique. Therefore, all participants see the same medical data sets. To compare the Phong and Outline visualization techniques without learning bias, we developed two evaluation versions for each method, one beginning with the Phong shader and the other with the Outline shader.

6.1. Tasks

We selected two different tasks for participants to complete. For the first task, we chose a multiple-choice approach, where the users had to select the correct answer from two or three options. Participants should first assess whether the overall changes in growth or shrinkage are linear (evenly) or nonlinear (unevenly), see Fig. 4 (a).

In a follow-up question, they are asked how much the pathology has grown or shrunk for each pair of consecutive time steps, see Fig. 4 (b). This allows us to assess the growth rate and perceived size ratios. For each selected answer, the users had to indicate how confident they were. We used a 5-point Likert scale ranging from *very confident* to *not confident at all*.

The second task was to assign adjectives to the visualization according to the participants' opinions, see Fig. 5. This task is intended to give us qualitative feedback on the visualizations. The participants also have the opportunity to write down adjectives for the visualizations themselves. Finally, users were asked whether they preferred the Phong

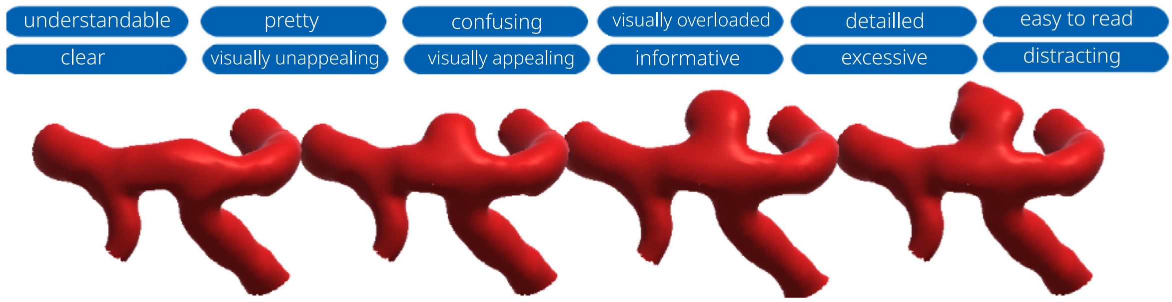

Fig. 5. Second task of our user study. Participants should assign adjectives to the visualization according to their opinions.

Table 1
Participant metadata shows a bias towards young participants with above-average levels of education and expertise in 3D and medical visualization.

Age		Gender		Education		Professional contact with medical topics		Professional contact with 3D visualization	
18–25	12	Male	15	Intermediate school	3	Never	13	Never	17
26–35	13	Female	24	High school diploma	8	Rarely	8	Rarely	6
36–45	1	Diverse	1	Vocational training	7	Sometimes	7	Sometimes	5
46–55	4	No answer	0	University degree	22	Often	2	Often	0
56–65	7					Very often	10	Very often	12
>65	3								

shader (color) or the Outline shader (contours) for solving tasks and for aesthetics. Since the study was conducted with non-experts, the words *Phong* and *Outline* were replaced with *color* and *contour* in the queries to make them easier to understand.

To solve the tasks, it is often necessary to rotate the 3D models, as the pathologies are hidden or difficult to recognize. We have implemented rotation buttons that can be held down to rotate the models left or right. For each task, we track whether the participants have used the rotation option. In the following, we describe the design of the tasks in more detail.

First Task. The possible answers for estimating the change in the size of two successive time steps are randomized in each case. The answer option that there is no change is always included. The second answer option is always the correct answer and the third is either twice or half the correct answer. The positions of the answer options and the fact whether twice or half of the correct answer is displayed as the last option is randomized. At the beginning of the evaluation, participants are shown an example task. The option to answer that there is no size change provides insight into whether participants notice size changes, even if they might misjudge the size ratios, and vice versa.

Second Task. We used a collection of twelve keywords, both positive and negative adjectives, and asked the participants to select the keywords they felt best described the visualization they were presented with. The keywords that can be selected in the second task are based on the word cloud from Garrison et al. [7]. Participants can select as many keywords as they like and there is also the option of writing their comments on the visualizations in a free text field. It is also possible to select none of the words.

7. Discussion of results

In the following, we discuss our results regarding the tasks, the usage of interaction methods, and preferences taking into consideration some study limitations.

7.1. Participants

Using the university mailing list, including a request to further distribute the study, we gathered 40 participants. They were asked about their age, gender, highest education degree, and professional experience with medicine and three-dimensional visualizations, see Table 1. Most of the participants (63%) are 35 years old or younger. About half of our participants are female (60%), and one participant is diverse or preferred to not answer the question. 22 participants (55%) have a university degree. More than half of the participants stated that they never or rarely dealt with 3D visualizations professionally. 10 participants (25%) stated that they deal with medical topics very often. All participants are from Germany. One of our participants has a red-green color vision deficiency. The participants show an above-average level of education and expertise in 3D and medical visualization. This is likely to influence the following evaluation results. We discuss the resulting bias in more detail in Section 7.3.

7.2. Tasks

As described in Section 6.1, the participants were asked to answer multiple-choice questions on overall growth and shrinkage rates and on the size change between successive time steps. Participants were also asked to select keywords that they thought describe the visualization best. Out of a total of 480 questions (120 for each sequence), 369 were answered correctly. 111 were answered incorrectly.

Growth Rate. Each participant was asked to assess the overall rate of size change of the pathologies shown. Since the study was conducted with non-experts, the words *linearly* and *nonlinearly* were replaced with *evenly* and *unevenly* in the queries to make them more accessible. Some participants reached out to us to provide feedback for the study where we found out that many participants understood the terminology differently. Some interpreted the term "evenly" as implying the absence of plateaus, while others correctly understood that the change in size was consistent only if the pathology expanded by the same factor at each time step. As we have not explained exactly how the terminology is to be understood, we can conclude with little confidence when analyzing this particular data. Since the growth of the models was never linear, the answer "The volume has grown evenly" was always incorrect. A very similar number of mistakes were made across all tasks for all shaders (around 34% of all answers were "even", although "uneven" was correct). However, we cannot say whether these results are due to differences in perception or a lack of understanding of the task.

Size Comparison. For the size comparison, one task consisted of three questions each on the differences between two successive models. The correlation between the error rate and the shader used can be seen in Fig. 6. In addition, the relationship between the type of size change (i.e. whether the pathology has grown or shrunk) and the type of

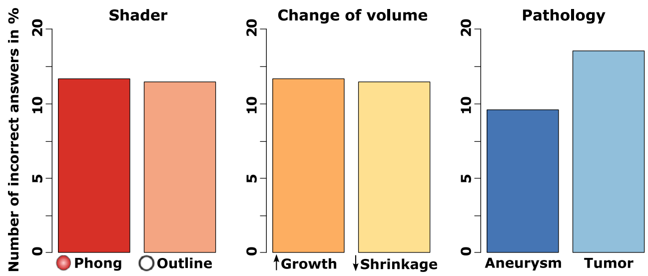

Fig. 6. Wrong answers per category out of a total of 480 questions.

pathology was also considered. The shader and the resizing had no noticeable effect on the error rate. The tasks in which a Phong shader was used had a similar number of incorrect answers (56) as those in which an Outline shader was used (55). When looking at growth and shrinkage of the pathologies, there is also no difference in the error rate. In the growth tasks, 56 errors were made, while in the shrinkage 55. A difference can be recognized when comparing the pathologies. The aneurysm tasks were answered incorrectly less often than the tumor tasks. This could be because the tumor was shown together with the surrounding liver. According to the experts, this context is important for the perception of the growth, but it can also lead to details being less visible due to concealment (e.g. by the vascular tree).

The questions on size comparison, in which the size of the pathology remained the same, were answered best. In total, there were only seven mistakes out of 80 answers. The shader was not a decisive factor here, as roughly the same number of mistakes were made for both (three and four, resp.). However, two particular questions caused some confusion regardless of the shader. To investigate this further, we observed whether participants tended to underestimate or overestimate the change in the size of the pathologies, see Fig. 7. In one case, participants were asked to answer whether the pathology was 32 or 64 times larger. This question was answered incorrectly 16 times, each time overestimating the change in size by a factor of two. Estimating size ratios of 3D objects is generally a challenging task, which is heavily influenced by the objects' shape [41]. Since the shape of the pathology has also changed significantly with size, this could be the reason for the high rate of incorrect answers to this question. Again, the shader did not influence the rate of mistakes. Both shaders produced roughly the same number of mistakes (eight mistakes for each shader).

However, while such a change in the error rate might be explained by the shape change, the second case yielded even worse results, being the only one, where the number of wrong answers was larger than the number of correct answers for both shaders. In this case, the pathology shrunk by a factor of four, but it was incorrectly estimated to be the factor of two by slightly more than half of the participants, as can be seen in Fig. 7, see (b) Phong and Shrinkage. Curiously, the participants had less trouble distinguishing between, for example, factors of three and six, which can be considered intuitively similar since both indicate the doubling in size. Because the liver tumor changed size relatively uniformly compared to the aneurysm, where only a portion of the structure changed volume, the ability to estimate size change may also have been confounded.

One notable outlier, where the size change was not correctly identified in six out of 20 cases, was in the case of both shaders for aneurysm growth. This may be explained by the initial position of the model, where the pathology is initially oriented towards the user. It is possible that the growth orthogonal to the screen was not comprehended well and thus, was underestimated when rotation was not used. Out of six participants, who answered incorrectly, only two rotated the model, which can be another reason for the larger number of incorrect answers. Since the aneurysm itself was also positioned on a curve, and also slightly changed the growth direction from one time step to the next, it could have made it more difficult to estimate volume. It is also possible that since we allowed rotation on one axis, the participants could not find the right angle to estimate the change in size. While the change in size was rarely correctly estimated, we assume that it was also used as a proxy for no answer since the study did not provide the option of not choosing an answer. Even in cases where a size change is obvious, as in the case of factor 32, there was still an answer indicating no size change (see Fig. 7).

Table 2
Relationship between correct answers and the use of rotation. For each pathology three tasks had to be solved per participant.

	All tasks correct	1 task incorrect	2 tasks incorrect	All tasks incorrect
Rotation	40	32	4	1
No rotation	34	36	9	4

Confidence. After each task, the participants were asked to indicate how confident they were. A 5-point Likert scale ranging from 1 (very confident) to 5 (not at all confident) was used. The error rates per visualization technique are shown in Fig. 8. Overall, most participants were most often confident or a little confident (113 out of 160 answers). Eleven times, participants were very confident. 26 times, they were not confident, and 10 times, they were not at all confident. In the tasks featuring the Phong shader, the participants were very confident more often in the case of growth compared to the outline shader. On the other hand, in the tasks featuring the outline shader, the answer *not at all confident* was given less frequently. Overall, however, the differences between the shaders are minimal. The distribution of answers is very similar and the error rate in connection with the participants' confidence levels is also similar for both shaders. There are also relatively few differences in confidence between the types of size changes. For growth, participants were more often confident about their answer (36 times) than for shrinkage (27 times).

The error rate and also the number of over- and underestimations are roughly the same for all shaders and growth and shrinkage as well. It is worth noting that it is difficult to estimate the correct volume change for a 3D model since the change in the diameter is way smaller, and thus the volume change might be easily underestimated. However, the distribution between participants who underestimated the size of the pathology and those who overestimated it is more or less even, with underestimation occurring slightly more often in 57 cases, while overestimation was observed 55 times. Thus, there was no significant trend in one direction. There were relatively few mistakes overall, however, the subjective perception of the participants seems to be somewhat different. Of the 69 times in which all three questions of the task were solved correctly, only 43% of the participants were confident or very confident that they had solved the task correctly. 57% were "a little confident", "not confident" or " not confident at all", although all questions were answered correctly. On the other hand, when answered "very confident", the participants also solved the task correctly in nine out of eleven cases. In the case of "not at all confident", the answer was incorrect in eight out of ten cases.

Use of Interaction Methods. The possibility of interaction (rotating the models around one axis) was used to solve 77 of the 160 tasks set. Each task consisted of three questions. We observed how often all of the questions were answered correctly or incorrectly and how often the rotation was used, see Table 2. We tracked whether the models of the time steps of pathology were rotated at all, but for each series of time steps, users had to answer three questions about the growth rate. Thus, the analysis of the relationship between rotation and the number of correct answers is limited because we did not track rotation for each subtask. We can see that participants who answered all three questions per task correctly used the rotation more often. Of the 72 cases in which all three answers were correct, 40 used the rotation, and 32

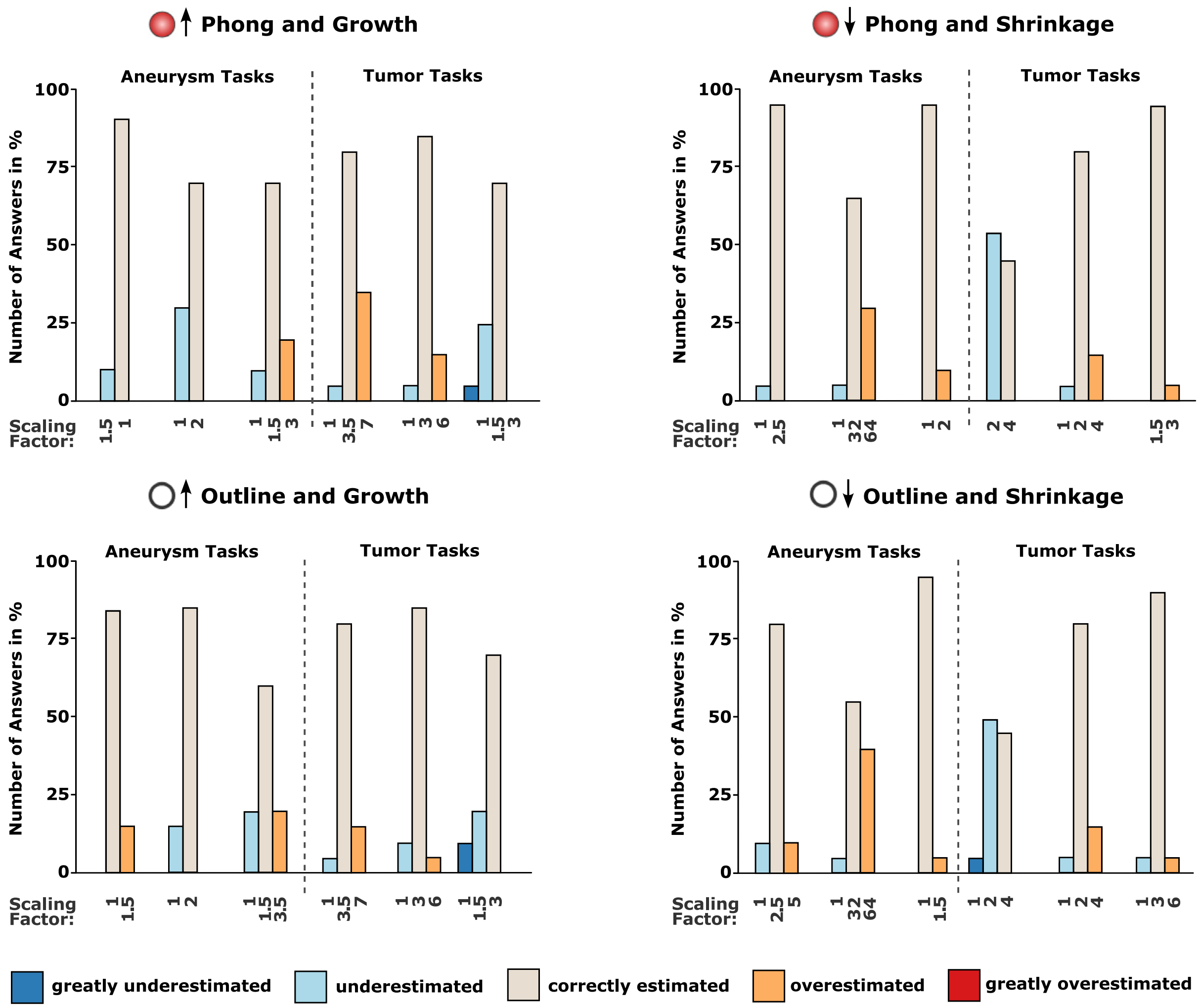

Fig. 7. Correct and incorrect answers for each task for each combination of shader and growth/shrinkage. For each combination, there are three tasks. Each task was completed 20 times. The scaling factors indicate the answer choices that participants chose, e.g., 1.5 means that the pathology grew or shrank by a factor of 1.5 compared to the previous time step. For each task, the scaling factors are shown to highlight the relationship between correct, underestimated, and overestimated volume changes and the actual factor by which the volume changed.

did not. People who answered all three questions incorrectly used the rotation less frequently. Four of the five cases in which all questions per task were answered incorrectly did not use the rotation. We observed that persons who did not use the rotation usually had at least one incorrect answer, with the number of those who did, constantly making fewer mistakes. Interacting with the objects, therefore, improved the correctness of the results.

The interaction was used more frequently for the aneurysms than for the liver tumors. This could be because the aneurysms are visibly tilted in one direction, so one can see that it needs to be rotated to get a better impression of depth. One other possibility is, that in cases of aneurysms, only a part of the structure grew, so the participants were more inclined to interact with it, while the whole tumor structure changed its size, which could have been perceived as uniform, and the possibility of interaction was disregarded. However, since the tumors were shown in the second half of the evaluation, it is also possible, that participants were less inclined to interact with the data. Feedback from individual participants indicates that many were frustrated with the study design, which we discuss in Section 7.3. We assume that 3D interaction, in general, is not intuitive for people who are not familiar with virtual 3D spaces, e.g., from playing video games, although we have simplified the interaction using buttons. Therefore, many users did not take advantage of the interaction opportunity even though it was explained at the beginning of the evaluation. However, we can conclude that interaction should be encouraged, even when dealing with a broad audience, since, according to our results, it improves the correct perception of 3D objects.

Keyword Selection. The results of the keyword selection were visualized in the form of a word cloud, as seen in Fig. 9. Both shaders were described as *clear* and *understandable*. However, most participants found the Phong shader *informative* and *easy to read*, as well as *pretty* and *appealing*, while the Outline shader was described as *unappealing*, and also often as *confusing*. The Outline shader has generally received more negative feedback, especially in regards to being visually pleasing. For the Outline shader, the word *unappealing* was used 23 times in comparison to three times for the Phong shader. Twelve participants considered the Outline shader to be *pretty*, while the same keyword was selected 20 times for the Phong shader.

Additionally, the Phong shader was described as *detailed* 17 times in comparison to the Outline shader (six times). In contrast, the Outline shader was also described as *distracting* and *visually cluttered*. However, it should be noted that in the case of the liver tumor, the surrounding liver model was rendered transparently, which might have influenced the opinion that it was *visually cluttered*, since one can see two shaders in one scene competing with each other. With that insight, we concluded that participants tended to describe the Phong shader

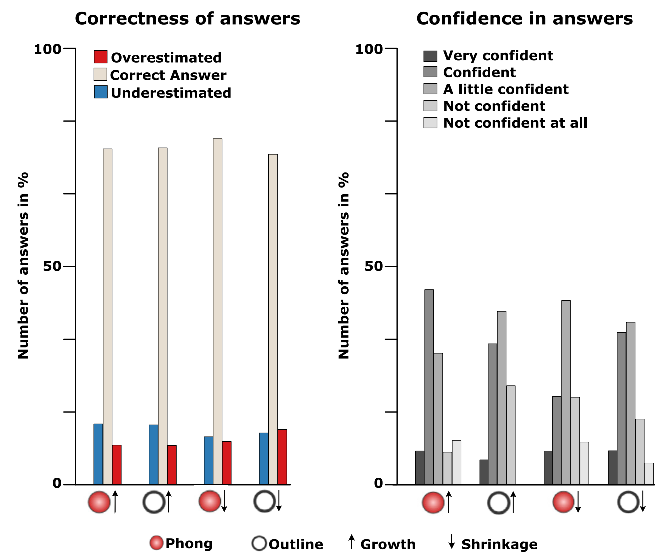

Fig. 8. Overestimation and underestimation of growth and shrinkage factors per visualization technique (left) and self-reported confidence in the answers given (right).

Fig. 9. Keywords are chosen by participants to describe a particular shader, colored and sorted in descending order of how often they were chosen.

more positively, and saw it as more aesthetically pleasing and easy to comprehend.

Shader Preferences. During the study, the participants were asked twice (once after solving the tasks for the aneurysms and once after the liver tumor) to evaluate which shader they found more aesthetically pleasing and which shader they found more suitable for solving the task at hand. Regarding aesthetics, Phong was found more visually appealing, with 71 votes compared to nine votes for the outlines of both pathologies. There are hardly any differences in preferences between the pathologies. For the liver tumor, five more study participants preferred the outlines. Phong was also preferred as help for solving the tasks. Out of a total of 80 votes, 65 were cast for Phong and the remaining 15 for the outlines. Comparing the data we collected on which of the shaders participants preferred, we can conclude that the Phong shader is generally considered to be more visually appealing, while still being informative and coherent enough to convey the information at hand. This statement is also consistent with the hypotheses of the doctors we interviewed about the study. Both expressed a preference for the Phong shader over the Outline shader. Although the Phong shader was seen as more favorable, compared to the Outline shader, this does not necessarily mean that the Outline shader can never be used to educate the general public about pathological growth. One participant with a red-green color vision deficiency stated that he was able to see significantly fewer details with the red Phong shader. Outlines could therefore be very useful for barrier-free accessibility.

7.3. Reflections on study design and limitations

In this section, we reflect on our study design, noting limitations concerning our design space, participant representativeness, and dropout rate.

Dropout Rate. 20 people dropped out of the study prematurely. In some cases, there was feedback that the tasks were too difficult for them (especially older participants). This likely introduces a bias survival problem, leading the study results to focus disproportionately on successful participants and neglecting failures. It also leads to a skewed demographic profile of our participants towards young people. There was also criticism that the study could not be carried out on a smartphone, which is another reason why people discontinued the study after being informed accordingly. In general, participants of all ages reported that the study was not exciting and that some of the tasks were found to be too difficult, so boredom and frustration are reasons for dropout that apply to all potential participants.

Participant Demographics. We conducted a user study aimed at a general audience. The people who chose to participate tended to be young and highly educated, and many had prior knowledge of medical topics. As a result, the composition of our participant cohort does not reflect a representative cross-section of the broader population. One likely reason is that our primary resource for acquiring participants was university mailing lists. Because the same bias affects participants in all versions of the story, the results remain comparable between different tasks and visualizations within the study. However, study results may vary significantly for audiences with different demographic backgrounds.

Data collected. Collecting additional data would have allowed for a deeper analysis of user behavior, reducing biased results due to poor design choices. First, a formative or pilot study could gather initial information to ensure the usability of the general study, such as whether the rotation buttons were used consistently by participants. In addition, tracking not only whether the rotation buttons were used but also to what extent provides further insight into how the use of rotation affects study outcomes. More detailed demographic data, such as the participant's occupation to determine what they are skilled at in a professional context, can further help interpret results and identify biases and differences between audiences.

Significance. Our study was exploratory, designed to observe trends and gather qualitative feedback on the use of the two shading techniques. The small sample size does not provide the robust data required for meaningful statistical analysis, particularly for detecting significant differences between the methods.

Design Space Limitations. Due to the enormous size of the design space for displaying surface models of anatomical structures over time, we had to set limitations in our study. Previous work on medical visualization of volume data provides a rich set of visualization techniques [18,42]. We have selected a small subset of two techniques, some of which are also used in educational textbooks, e.g., illustrative techniques. Additionally, we decided to present discrete time steps to the participants which were shown side-by-side. Alternative presentations of time steps are also possible, for example, an animation that switches between time steps automatically or to create the impression of continuous growth by morphing the 3D meshes when switching between time steps. A self-playing animation would not adapt to the users' speed and only go forward. Therefore, it might be more difficult for users to solve the tasks. We implemented interaction in the form of rotation around one axis using buttons , as this is an easy-to-use interface element that is widely used in many applications and, therefore, familiar to most people. Following these arguments, we drastically narrowed down our design space, focusing on which shader variant is preferred, which performs better in terms of correct answers, and whether the option to rotate the models is used at all.

Artificially Generated Data. The models we are using for the time steps are manually created. Only the last time step of each data set showing the full-grown pathology is derived from data. Therefore, the other time steps might not depict how the pathological structure evolved in reality. However, realism is not a major factor in this study and after consultation with two physicians, the suitability of the models for the general public was confirmed.

8. Conclusion and future work

By adapting the study design compared to our previous study, we were now able to compare the use of Phong shader and outline shader for medical 3D data targeted at lay audiences in more detail. By assessing both performance on the task and self-reported observations in the form of keywords, we were able to separately investigate which visualization technique helped participants better evaluate the data and how participants perceived the visualization techniques. Especially the latter was not included in our prior study but plays an important role when communicating data to a lay audience.

Both the Phong shader and the outline shader were generally successful in showing the growth and shrinkage of pathologies. As indicated by medical experts in our pre-study interview, the aspect of growth is very important for the general public to understand, while the speed is less important since such details are usually discussed in a medical setting under the supervision of experts, for example, in discussing possible therapy or care. Our study results indicate that the Phong shader seems to be more popular with the general public. However, the outline shader performed especially well for one participant with red-green color blindness. Further research could investigate the aspect of accessibility when creating surface visualizations for a broad audience.

Our user study showed that the participants performed rather similarly, regardless of the shader they were presented with and if the pathology was growing or shrinking. Future studies are needed to investigate further visualization techniques or additional variants of illumination-based and illustrative techniques. An interesting parameter to include in such studies would be task completion time to measure not only the accuracy but also the efficiency of solutions. Since aesthetics is an important aspect of visual communication, this would shed more light on which visualization technique should be implemented in data-driven stories. According to our results, using the Phong shader as the default but offering the possibility to switch to, e.g., an outline shader, would be the best option to act according to user preferences while providing accessibility, e.g., for colorblind users.

We observed that participants gave more incorrect answers to questions about liver tumors than about aneurysms. Aneurysms may be easier to assess because they grow or shrink in one main direction, while tumors grow and shrink in all directions. To further enhance the interpretability of the aneurysm models, a visualization of where the healthy vessel structure ends and the aneurysm begins can be provided.

Incorrect answers were more frequent when the participants did not rotate the models. Even though we changed the way users can use the rotation compared to our previous study, this remains an issue where future work is needed to investigate how to facilitate the use of 3D interaction for laypersons. However, if a surface visualization is designed to force users to interact to understand the visually conveyed message, it can lead to frustration if they do not master the interaction techniques provided or if the interaction is perceived as cumbersome or tiring. On the other hand, it can also be a way to efficiently introduce an audience to 3D interaction techniques and motivate their use.

The dropout rate of our study was rather high highlighting the need to improve the study design. To avoid frustration among participants, the explanation of the tasks could be improved, e.g., textual explanations and introductory videos could be included. In the future, a formative evaluation with a small number of participants should be carried out before a study is launched to ensure that the explanations, terminology, and interaction opportunities are understandable. In addition, to make the study more exciting and prevent users from dropping out due to disinterest, gamification elements could be included, such as displaying the number of correctly solved tasks after each pathological case is completed. Nehring et al. [43] showed that gamification is an effective method to counter a lack of motivation in an educational context.

Aneurysms, as well as tumors, can create bulges, so-called blebs. For aneurysms, these blebs are often associated with an increased risk of rupture while an irregular shape indicates that a tumor is malignant. Therefore, blebs are critical in assessing the pathology. Future studies should investigate how to convey not only the change in size but also the change in shape over time. For implementing user studies investigating how to communicate morphological changes of pathologies, realism is more important than for investigating the perception of size differences. Therefore, mathematical growth models can be used to generate realistic time steps of pathological changes [28–30]. On the other hand, further studies could investigate the influence of surface complexity on the difficulty of certain tasks. Therefore, anatomical structures could be further abstracted, e.g. using spheres.

Our study investigated static, discrete time steps for non-periodic time-oriented medical image data. However, temporal changes can also be shown using animations. Therefore, future research is needed to investigate if animations can support users in understanding and analyzing growth processes. In addition, appropriate interaction techniques for continuous animation should be explored, especially concerning the ability to steer the animation according to the user's personal needs. In the context of growth and shrinkage, further studies could investigate whether the use of 3D models is the optimal solution for lay educational materials, or whether other visualizations, such as line graphs, are more appropriate.

CRediT authorship contribution statement

Sarah Mittenentzwei: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Sophie Mlitzke:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Darija Grisanova:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kai Lawonn:** Writing – review & editing, Resources. **Bernhard Preim:** Writing – review & editing, Supervision, Conceptualization. **Monique Meuschke:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Conceptualization.

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.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

The supplementary material contains a video of one evaluation sequence and the evaluation data. Additionally, it can be found online.

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cag.2024.104023.

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