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Visualizations for Hierarchical Data: Analyzing User Behavior and Performance with Eye Tracking

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***Abstract*—Visualizing hierarchical structures is of great importance in many economic and scientific applications. Many different approaches have been developed and enhanced in the last decades. Each of them claims specific advantages over competing methods, usually referring to visual or structural properties. Although several user studies investigated the usefulness of specific approaches, for practitioners it often remains unclear what the practical advantages of the approaches are and in which contexts they are useful. In our user study, we systematically investigated the value of three frequently used visualization types for the intuitive understanding of hierarchical data: treemap, icicle plot, and nodelink. We measured user performance in terms of correctness and time and tracked eye movements for each participant. The results regarding the user performance revealed that nodelink and icicle plot performed well, whereas treemap only exceeded chance level in one easy task. Still, the analysis of eye-tracking measures suggests that treemaps draw visual attention better to relevant elements. However, treemap visualizations built up less influential visual gaze patterns, compared to nodelinks and icicle plots. Finally, implications for facilitating human intuition and problem solving strategies are discussed.**

***Keywords*–User Study; Hierarchy Visualization; Perception; Eye-tracking; Eye-gaze Patterns.**

I. INTRODUCTION

This paper is an extended version of a work, recently presented at the International Conference on Advances in Computer-Human Interactions (ACHI) [1]. First results of the reported study were already presented at the EuroVis Workshop on Reproducibility, Verification, and Validation in Visualization (EuroRV^3) [2]. In this paper, we report an extended and more thorough analysis, including the investigation of eye-gaze patterns. The main objective of the study was the research of visualizing hierarchical data, which has a long tradition going back to the drawings of medieval family trees. A wide research field with very different visualization approaches developed over the last three decades, investigating a multitude of different visualization properties and aiming at all kinds of different applications. However, despite this long tradition there are still new developments in the field through new applications and demands [3], [4], [5], [6].

A comprehensive overview over most of the proposed hierarchy visualization techniques is maintained by treevis.net [7], [8]. Every approach was published with several advantages in mind and was at the time of publication an advancement to the state of the art. However, apart from their professional experiences, practitioners have no objective benchmarks to decide, which new (or even older) visualization fits their needs best.

This issue becomes even more eminent considering the importance of hierarchical data structures in science [9], [10] and economy [11], [12], where visualizations can significantly influence large-scale decisions [13]. For example, Vliegen et al. [14] presented different applications of treemaps to business data. They found that in general there are too many parameters to set and tune in standard visualizations and concluded that users need custom solutions, specifically designed by visualization experts. Especially in this environment, where decisions can have drastic consequences and frequently have to be made in a short time frame, users need to understand the properties and shortcomings of visualizations to be aware of possible implications.

In this paper, we make a step towards studying which visualizations are intuitively understandable by non-experts. To this end, we investigate how different visualization techniques impact the users' understanding of the data. Since we treat visualizations as objectively as possible, our goal is not to show which visualization is superior, but to understand what problems and pitfalls arise when non-experts use different visualizations to solve typical tasks.

We restricted our study to static and non-interactive visualizations. Apart from being much easier to interpret, especially when analyzing problem solving patterns, they are highly relevant, since many practitioners mainly rely on static visualizations on paper or digital presentations to convey their data. In most cases, it would be just too cumbersome for non-visualization scientists or managers to run an interactive session with a visualization software just to understand their data and results of related scientists or competitors. Therefore, we also excluded all pure visualizations heavily relying on 3D metaphors. They always require at least basic interaction capabilities to produce meaningful results. Since Burch et al. [15] showed that radial techniques [16] for the visualization of hierarchies are understood less intuitively, we further restricted our study to linear visualization techniques. After a thorough analysis of several well-established reporting and analysis software packages, we decided to compare nodelinks, treemaps, and icicle plots, because they represent the most common visualization techniques.

In addition, we restrict our considerations to the area of visualizing hierarchical data with additional scalar dimension, which is highly relevant especially in the business environment. More precisely, the data consists of a rooted tree $T = (V, E, v_{\mathrm{root}})$, where V is the non-empty set of data elements (nodes), E is a subset of $V \times V$ representing the hierarchy relations (edges), and $v_{\mathrm{root}} \in V$ is the root node of the hierarchy. Additionally, a function $f : V \rightarrow \mathbb{R}^+$ is given, which assigns each node a specific positive value and respects the hierarchy. More precisely, the sum of function values of all children of a node is always smaller or equal than the function value of the node. One example for such data is a company structure with annual expenses.

In Sections III and IV, we present background about the tackled visualizations and the relations to cognitive science. We give a precise description of our study setup in Section V. In Section VI, we present a detailed analysis of the results of the user study with respect to participants' performance and eye-gaze data.

II. Related Work

General design rules for good visualizations have been intensively discussed in the last decades and are often based on the investigation of visual attention [17], [18] and the understanding of the human cognitive system. In this regard, the effects of colors in visualizations received much research attention, because they represent a particular powerful visual cue [19], [20], [21], [22]. A comprehensive overview about those design rules and general strategies was presented by Ware [23].

One of the most-used practical examples when visualizing hierarchies with an additional scalar component is the file system of computers. Stasko et al. [24] evaluated the two visualization techniques treemap [25] and sunburst [26] with respect to their capabilities for standard file-management tasks, like locating files or comparing file sizes. They measured user performance by logging their number of correct answers and their reaction times. They found that sunburst significantly outperforms the treemap representation, presumably because of the more explicit representation of hierarchy relations in sunburst.

In a very similar study, Bladh et al. [27] evaluated the usefulness of encoding the depth of nodes in a treemap using the third dimension in comparison to a traditional treemap visualization. Again, users had to complete typical file-management tasks. It turned out that both visualizations were not significantly different in most tasks, i. e., the third dimension did not result in a performance loss due to the additional navigational and cognitive efforts. However, users' performance was significantly better with the 3D visualization when having to identify the node with the highest depth in the hierarchy.

Wang et al. [28] had a similar experimental setting by comparing a standard file browser to rings [29] and treemap [25]. They evaluated the effectiveness of the methods based on complex questions, such as finding two similar directories or the most homogeneous directory. The users' performance was measured by assessing their answering time. Additionally, they were asked to rate the difficulty of each question with the respective visualization. In summary, the file explorer performed significantly worse than both other methods with no significant difference between rings and treemap.

Ziemkiewicz and Kosara [30] showed that the methaphoric presentation of tasks influences users' performance during the work with hierarchy visualizations. In our study, we followed this findings and extended the scope by formulating the tasks abstractly with respect to the hierarchy.

Borkin et al. [31] presented a new method for visualizing filesystem provenance data, which relies on a combination of a radial-based tree layout and a time-based node grouping. The system was evaluated with domain experts and compared to a state-of-the-art nodelink tool [32] by measuring accuracy and efficiency. Results show that the new tool outperforms the state of the art. A very interesting additional finding was that there was a significant gender effect in the state-of-the-art method, which was not the case for the proposed method.

Teets et al. [33] stressed the need for evaluation of the effectiveness of visualizations especially in the business environment. They analyzed a very specific application in the field of process monitoring, which was based on production data of a can factory. Their evaluation relied on cognitive fit theory, i. e., they investigated how good the visualizations and induced mental models fit to the problem solving strategies. They found no information loss when not displaying accurate values in a tabular fashion as well as a significantly faster solution time when using visual representations.

While most studies rely on user performance data in terms of the number of correct answers and reaction times, eye-tracking studies have been the exception. However, Burch et al. [15] investigated the impact of different layouts of nodelinks using eye-tracking. They used one question type and an explanatory task. The users were confronted with two different linear layouts with four different placements of the root node and a radial layout of the nodelink. Burch et al. assessed both eye-movements and performance data, allowing to systematically compare the results from different measurement approaches. The users performed much better with the axis-aligned layouts than with the circular one, which might be a result of the typically linear fashion of information display, the users are familiar with. In line with this argument, the traditional layout with the root node at the top performed best, which further emphasizes the role of individual experience with visualizations in understanding them intuitively and using them for problem solving.

A recent variation of the treemap design is the angular treemap [34] with the goal to enhance comprehension of hierarchy levels by rotating parts of the treemap. Liang et al. [35] conducted an experiment comparing traditional and angular treemaps. The study mainly investigated search tasks and measured completion time. While it turned out that the new design was significantly better, the flexible method needs several well-tuned parameters and, thus, should be set up by visualization experts to achieve comparable results.

III. Visualizations for Hierarchical Data

The need for visualization expertise is true for many new and sophisticated visualization techniques. However, there

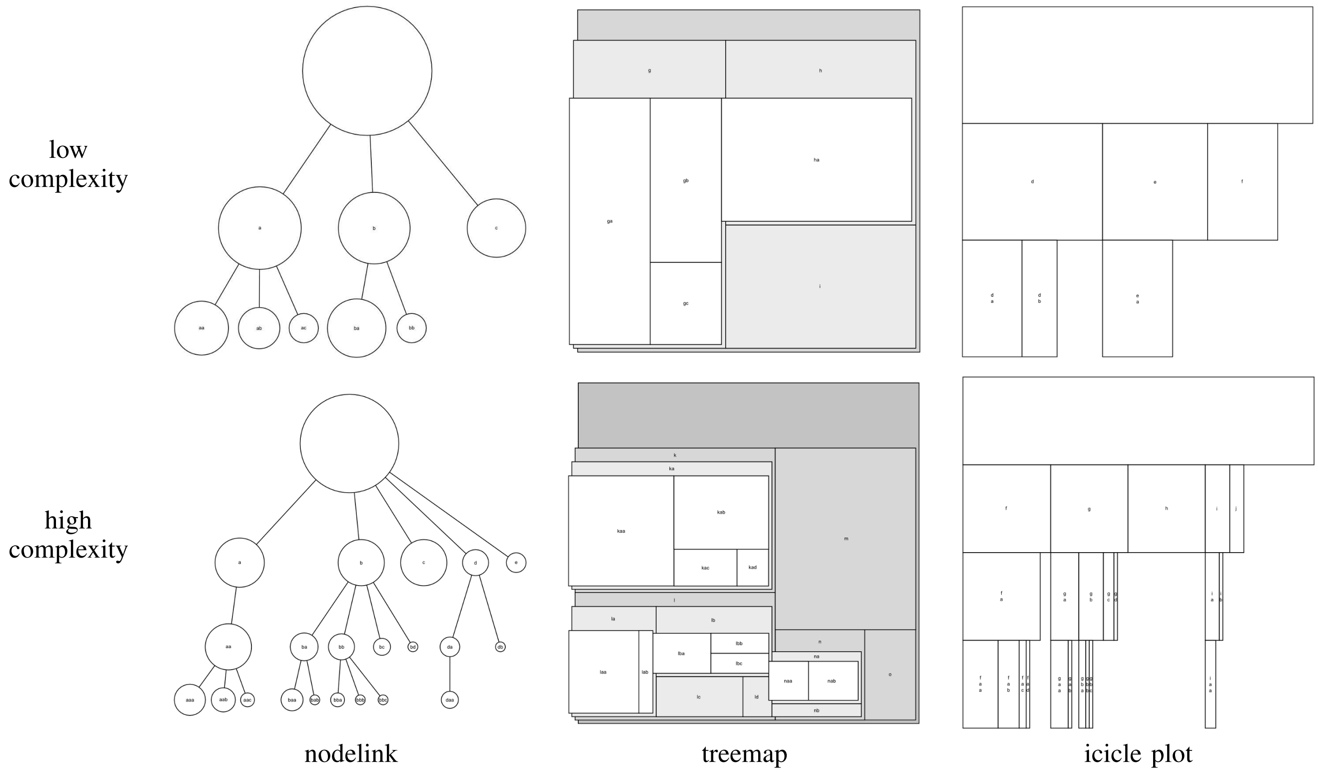


Figure 1. Example stimuli that where used for the user study. For each of the four questions, we presented three different visualization types (nodelink, treemap, icicle plot) of equivalent hierarchies with additional scalar values per node. In addition, we varied the complexity of the hierarchies, resulting in visualizations with low (height two, maximum three children per node) and high complexity (height three, maximum five children per node).

is an ever growing demand for easily usable and reliable visualization techniques for hierarchical data in practice that can be used without much prior knowledge. Therefore, we wanted to investigate the properties of three of the most-used and practice-relevant visualization techniques for hierarchies with additional scalar dimension. We intended to investigate these visualizations with respect to fast and accurate data comprehension for users with low visualization knowledge and only a short time of familiarization with the type of visualization. After elaborate inspection of the treevis repository [8] and several software packages for productive use [36], [37], [38], [39], we decided to compare nodelinks, treemaps, and icicle plots. Illustrations of the investigated visualization methods are given in Figure 1.

The use of nodelinks for drawing trees is very intuitive since it replicates the structure of botanical trees. Consequently, nodelinks have already been used for ages to represent hierarchies and the research on optimal drawing of nodelinks has a long tradition [40]. The strengths of the nodelink representation are its intuitiveness and clear representation [41]. However, many competing techniques produce less empty space and allow a more integrated visualization of the additional scalar dimension.

The concept of treemaps, as one of these presumably superior techniques, has been introduced by Johnson and Shneiderman [25]. Since then a lot of different modifications, additions, and enhancements were proposed [42], [43], [44], [45], still respecting the initial idea of maximizing screen space usage and implicit encoding of the hierarchy. These aspects are often referred to as the main advantages of the concept. Problematic properties, which are nowadays still constant topic of further research [46], are the inherent overplotting, problems with hierarchy perception, and complications with node distribution.

The icicle plot is another concept with a long tradition and was originally proposed by Kruskal and Landwehr [47] for the display of cluster hierarchies and based on the trees and castles of Kleiner and Hartigan [48]. Although it has been shown that users perform worse, when using radial layouts [15], icicle plots are used less often in practical applications [49], [50], [51] than their radial counterpart, the sunburst diagram [26], [52], [53], [54]. Sometimes not even the correct name for this linearized sunburst is used. Still, the icicle plot combines two strengths of nodelink and treemap, namely the intuitive top-down design and the implicit hierarchy encoding. In addition, it inherently features a one-dimensional encoding of the additional scalar dimension. On the other hand, the screen-space usage is less efficient compared to treemaps.

IV. Cognitive Processing of Visualizations

Assessing the effectiveness of visualizations, requires to distinguish between the visual search phase and the stage of central information processing. In the visual search phase, the user has to identify relevant elements of a visualization. During this process the user constantly reallocates the attention to different elements of a visualization. Following Schneider and Shiffrin [55], [56], this process can be characterized as an interplay of bottom-up (automatic) and top-down (controlled) attention allocation.

Our visual field can be considered as an assembly of elements competing for our attention [57]. Bottom-up processes are triggered by elements, which stand out from their environment. A node of a visualization could for example be colored differently or have a different shape compared to other elements. This type of attention allocation is highly automated. Top-down attention, on the other hand, is moderated by the user's intention and previous knowledge. For example, when the user's goal is to compare two elements of a visualization, the user employs a strategy of visual search, during which the positions of all relevant entities are identified. The search process itself can be carried out both by chaotically searching for relevant elements (bottom-up) or deducting the relative position of an element from other elements through previous knowledge about the type of visualization (top-down) [58]. The first strategy is suited for users without any previous knowledge and its efficiency depends on the visualization's complexity. The latter strategy, however, can be employed by users, who understood the basic principles of a visualization, and should result in a more efficient use.

As we can only observe eye movements by users, we are usually not able to distinguish between bottom-up and top-down attention allocation. Both mechanisms directly impact which elements our eyes fixate. Additionally, the mere fact that users fixate an element of a visualization does not imply that this element is being processed centrally. Moreover, it does not even imply that the user is looking at the element, because attention can also be allocated towards elements outside of central vision [59]. Although we are not able to see elements as clearly when using peripheral vision, humans are still able to estimate object shape and size rather accurately when distributing visual attention over a larger area of the visual field. If, however, we were able to observe reoccurring patterns of eye-movements, both within users and between users, we can be sure that these patterns represent phases of top-down attention allocation. Visualizations that produce this kind of reoccurring patterns can be considered as an efficient means of data display. Thus, one important goal of the current study was to extend existing research by employing eye-tracking not only to count and compare fixations, but to investigate transitions between visualization elements as well as reoccurring fixation patterns.

When the relevant elements of a visualization are identified, the user enters the stage of central information processing. The success and the efficiency of a visualization depend both on user and visualization properties. User properties affecting visualization processing are most likely previous knowledge about the type of visualization, general intelligence components, especially those related to visual-spatial information processing, and possible impairments (e.g., color or stereo blindness). In terms of information processing, nearly all properties of a visualization, like color usage, descriptiveness, intuitiveness, alignment, or visual data preparation affect success and efficiency. In this paper, we assess indicators for both phases of visualization processing. While performance data allow the empirical investigation of the information processing phase, eye-tracking and reaction times enable the investigation of the visual search phase.

V. METHOD

We conducted a laboratory experiment, during which participants had to solve problems using different visualization techniques. For each participant, the performance in terms of accuracy and completion times as well as eye movements were recorded.

A. Stimulus Materials

We employed a $3 \times 4 \times 2$ within-subjects factor design with visualization type, task, and hierarchy complexity as independent variables.

1) Visualization Types: All hierarchies with additional positive scalar values per node were visualized using three different visualization types, illustrated in Figure 1. The nodelinks were generated using Reingold and Tilford's algorithm [40]. The additional scalar value per node was indicated by the area of each node's circle. As for all three different visualization types, each non-root node was annotated with an alphanumeric code to allow for unique identification by the users. The treemaps were generated using the squarified approach [44], again encoding each node's scalar value by area. To enhance the perception of different hierarchy levels, nodes were color coded in different grey scales and, following Bladh et al. [27], stacked in a 2.5D fashion. The icicle plots were generated in the top-down fashion that is used most often. Screen space was divided in rows of equal height, depending on the height of the hierarchy. The root node's width was set to the full width. For each node, all children were drawn below the node with a width proportional to the scalar values, respectively.

2) Tasks: We interviewed several researchers from different fields of economics and social sciences, who regularly deal with hierarchical data. In most cases, they seek to understand the hierarchical structure, which means understanding the relation between nodes, comparing the values of different nodes, or counting nodes or leaves of trees or subtrees. We identified four tasks, which are commonly performed when confronted with the given visualizations. From these tasks, three are hypothesized to favor one of the visualization types, respectively. For the fourth tasks, we could not find any strong indications on what visualization might be favored and added it as an exploratory task. In detail, the tasks were:

- T1: Count all leaf nodes of the hierarchy.
- T2: Count all nodes of the hierarchy.
- T3: Compare the combined area of two pairs of nodes within one level of the hierarchy.
- T4: Compare the combined area of two pairs of nodes across different levels of the hierarchy.

The tasks differ in difficulty: Counting leaves and nodes is less cognitive exertive than comparing the sizes of nodes. However, this does not affect our main goal, the analysis of differences between the visualization methods.

3) Hierarchy Complexities: As base data set we used two artificial hierarchies with different levels of complexity. The hierarchy with low complexity had height two and had a maximum of three children per node. In contrast, the height of the hierarchy with high complexity was three with a maximum number of five children per node. An illustration of the different complexities can be seen in Figure 1.

Since the hierarchy for all visualizations was initially equal per complexity level and question, it could have happened that participants remembered their choice from a different visualization and just replicated it. To overcome this problem, we slightly changed hierarchies (changed size of one node or added/removed one node/leaf) for each visualization of one complexity-task combination. Consequently, tasks and answers were not equal per visualization but still comparable in terms of difficulty. Participants were informed that similar hierarchies might not always result in the same answers.

B. Hypotheses

From a review of relevant literature and recommendations in software packages, we extracted several claims of what benefits the used visualizations should have. Together with the tailored questions, this resulted in the following hypotheses, which we wanted to check with our experiment.

- H1: Task **T1** favors the treemap over both other visualization types.
  Counting leaves on a treemap reduces the task to simply counting all non-occluded rectangles. Users have to traverse the whole hierarchy to count the leaves in both other visualizations.
- H2: Task **T2** favors the nodelink over both other visualizations.
  Counting nodes is reduced to simply counting all circles in the nodelink visualization, which are, even in contrast to the icicle plot, clearly distinguishable from background and auxiliary lines.
- H3: Task **T3** favors the icicle plot over both other visualizations.
  Comparing sizes of nodes within one level of the hierarchy should be easier when comparing lengths on one straight line using the icicle-plot visualization. In contrast, users have to sum up and compare areas of different proportions when using a treemap and, even more difficult, sum up differently-sized circular areas in the case of the nodelink.
- H4: Treemap performs worst in the tasks **T1**, **T3**, and **T4** due to overplotting.
- H5: When only varying hierarchy complexity, users perform better with the low complex hierarchy compared to high complexity.

C. Sample

We recruited $N = 69$ second year university students of the local communication studies program (age: $M = 21.09$, $SD = 2.40$, female = 53). The students were well-skilled in reading academic publications and working with statistical analyses and charts. Apart from their general experience, they had no specific knowledge in either of the presented visualization methods nor in visualization of hierarchies in general. They received study credit for their participation.

D. Procedure

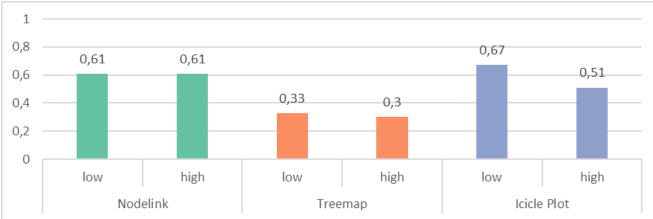
To control for sequence effects, we generated two different pre-randomized sequences respecting a non-repetition restriction. Each participant was assigned to one of the sequences in which the combinations were presented, respectively. Both sequences did not differ in their performance ($t(67) = -0.238$, n.s.). The hierarchies were presented on a 19” computer screen with a resolution of 1280×1024 pixels via E-Prime 2.0. An SMI RED eye-tracker from SensoMotoric Instruments was installed below the screen and recorded eye movements at 50 Hz. The stimuli were presented at a head distance of about 700 mm. However, due to the contact-free setup, slight variations of the distance during the experiment were possible, which should not affect the results due to the within-subjects factor design, and the SMI hardware being able to compensate for movements. All participants were calibrated using a five point matrix according to the standard SMI RED setup procedure. Each event in E-Prime was logged within the eye-tracking data file, which allowed to synchronize stimulus presentation and eye-tracking data. In the first part of the instructions, the definition of a hierarchy, the difference between leaves and nodes, and the different types of visualizations were explained to the participants by showing examples. They also received a speed-accuracy instruction (i. e., “Please answer as quickly and accurately as you can!”).

During the experiment, participants were first shown a textual description of the task (e. g., “How many leaves does the hierarchy have?”) as well as the possible answers and then had to press a key to proceed. This allowed each participant to read and understand the task and the answers at her own pace. Next, the hierarchy visualization was presented in addition to the task and the answers. Participants then had to respond by pressing one of three answer keys, with one correct answer and two distractors, resulting in a chance level of $p = 0.33$. E-Prime automatically logged the participant’s answer and completion time, i. e., the time of stimulus onset until the participant’s response. In average, the response time for an item was M = 19.6 sec (SD = 5.9). This procedure allowed us to be able to judge users reaction times without the delay of having them typing in the correct number. First, all participants were shown a training sequence of the visualizations. Afterwards, all three visualizations in both the high and low complexity were presented. Nodes to be compared were named in the question before the visualization was shown and remained visible during the task until an answer was given. The whole procedure took less than 25 minutes per participant. After the computer test, participants filled out an electronic questionnaire with items concerning manipulation checks and demographic data.

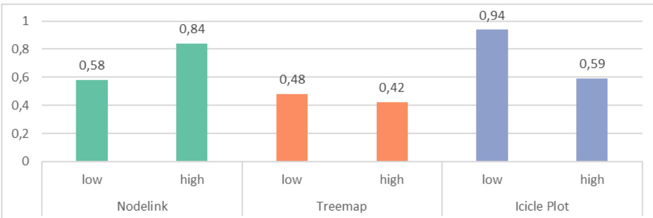
VI. RESULTS

We recruited undergraduate students from Chemnitz University of Technology, and therefore, conducted the study with a very homogeneous set of participants. Thus, demographic assessments did not show any correlations or other interesting variables regarding age, gender, or occupation. A plot of the participants’ performance with respect to the independent variables is shown in Figure 2.

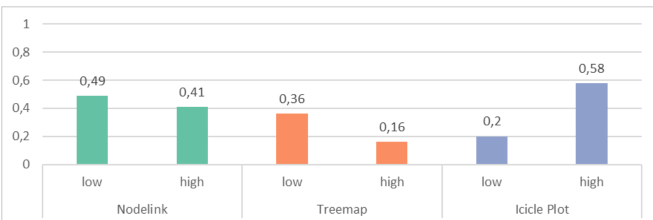
To test our hypotheses, we used a $3 \times 4 \times 2$ repeated measures ANOVA (analysis of variance) with participants’ performance as dependent variable. Alpha levels for all calculations were set to $p < 0.05$. Due to the violation of the sphericity assumption, Greenhouse-Geisser-corrected dfs are reported, when necessary. We found a significant main effect for the type of visualization ($F(2, 136) = 53.77$, $p < 0.001$, $\eta^2_{\text{part}} = 0.442$). More specifically, performance was significantly lower when using treemap compared to nodelink and icicle plot, whereas the latter two did not differ significantly. Participants performed well above chance level with both nodelink ($M = 0.55$, $t(68) = 8.73$, $p < 0.001$) and icicle-plot visualizations ($M = 0.54$, $t(68) = 9.03$, $p < 0.001$). However, participants did not perform above chance when presented the



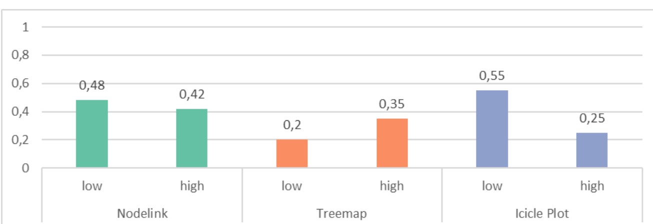
T1: Count Leaves



T2: Count Nodes



T3: Compare in Level



T4: Compare Between Levels

Figure 2. Plot of the average correctness of participants' answers to the four questions with respect to visualization type and hierarchy complexity. Chance level is at 0.33.

treemap ($M = 0.33$, $t(68) = -0.332$, n.s.). These first results validate hypothesis **H4**. Furthermore, we found that participants were able to perform above chance level only in task **T2** when using a treemap, i. e., counting nodes at low complexity ($M = 0.48$, $t(68) = 2.40$, $p < 0.05$). This discovery directly opposes hypothesis **H1** and lets the treemap stand out as the worst choice for all tasks. Even at its best performing task **T2**, nodelink and icicle plot performed significantly better ($F(1, 74) = 50.02$, $p < 0.001$, $\eta^2_{\text{part}} = 0.403$).

Results did not show a significant main effect for complexity of hierarchies, ($F(1, 68) = 2.607$, n.s.). Consequently it seems that, in the current setting, hypothesis **H5** can not be confirmed. However, revisiting the stimuli and analyzing the after-test feedback resulted in at least two possible factors influencing the results with respect to this hypothesis. One surprising fact is that participants performed significantly better with the complex nodelink compared to the less complex nodelink for task **T2**, counting nodes ($t(74) = -4.32$, $p < 0.001$, $\eta^2_{\text{part}} = 0.20$). It is apparent that some participants were uncertain if the root node is also counted as a node and, consequently, counted one node less. In the high complex stimulus, this was compensated, because, as all answering options were above their count, the participants simply chose the lowest possible answer, which was the right one. In the low complex stimulus, this strategy did not work, as indicated in Table I. Due to this occurrence, it is not possible to validate hypothesis **H2** although the performance of the nodelink is still significantly better than both other visualizations when only using the complex hierarchy ($F(1, 74) = 32.85$, $p < 0.001$, $\eta^2_{\text{part}} = 0.307$).

TABLE I. OBSERVED RELATIVE FREQUENCIES FOR TASK **T2** USING NODELINK REPRESENTATION. FOR LOW AND HIGH COMPLEX HIERARCHIES, THE CORRECT ANSWER IS RESPECTIVELY HIGHLIGHTED WITH GREY.

Answer	Low Compl.	Answer	High Compl.
7	6.8%	22	84.7%
8	34,7%	23	13.6%
9	58.5%	24	1.7%

We encountered another surprising result when we compared icicle plots of high and low complexity for task **T3**. Again, the less complex hierarchy is performing significantly worse than the complex hierarchy ($t(74) = -5.11$, $p < 0.001$). The performance is even significantly below chance level ($t(74) = -2.52$, $p < 0.05$), leading to the conclusion that the participants were confident in their (wrong) answers. After carefully inspecting the stimulus for the low complex hierarchy, illustrated in Figure 3, we assume that participants' confidence was based on a wrong assumption about the pictorial information. The Gestalt-laws [60] suggest certain cognitive grouping tendencies when confronted with images. Based on the Gestalt-laws of proximity, closure, and common region, the nodes da, db, and dc are perceived as belonging together. The task, however, asks to judge the combined size of the first two ($da + db$) against the other node and an "external one" ($dc+ea$). Due to this, we assume a misleading perception, which lets the participants underestimate the size of $da + db$. The cognitive process of "moving" area dc over to ea (or reverse) might be influenced by the distance between the two because of the impression that both nodes together (a gestalt) require more space due to the empty space between them. This overestimation could be the reason, why hypothesis **H3** cannot be supported, although in the high complex setting icicle plot performed, as predicted, significantly better than nodelink and treemap at **T3** ($F(1, 74) = 22.57$, $p < 0.001$, $\eta^2_{\text{part}} = 0.234$).

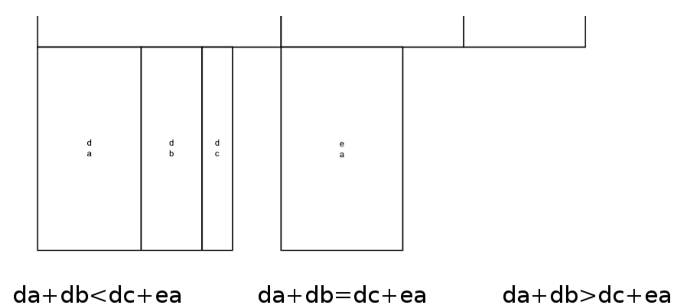


Figure 3. Close-up view of the stimulus for task **T3** using the low complex hierarchy and the icicle-plot visualization. The area $da + db$ is actually larger than $dc + ea$ but the latter is overestimated due to the empty space between both areas.

A. Heatmaps

Beyond looking into the participants' performance, we also recorded the eye-movement of all participants during the tasks. For the analysis, the areas of interest were defined with respect to each task of the study. Fixations were detected, based on 80 ms duration. After careful inspection of the heatmaps for each task, we decided to enlarge each area of interest by 20 pixels beyond the actual node to account for measurement error and peripheral vision when looking at rather small nodes (see for example Figure 6). As a first approach we analyzed the heatmaps of different tasks and visualizations and their evolution over time to gain insight into the participants' general search strategies and visual foci. The heatmaps were generated by accumulating fixations over a specified period of time and the calculation of the smoothed average density of fixations for each pixel. The resulting density function was color-coded in the range between minimum and maximum using the built-in color scheme of the eye-tracking software, depicted below:

In Figure 4, we illustrate the heatmaps for different subsequent periods of time for nodelink and icicle plot of the high complex hierarchy and task **T2**. The heatmaps suggest a top-down and left-right movement of participants' fixations, which is consistent with the top-down screen-space structure of the visualizations. This coincides with the expected gaze direction that is deeply rooted into cultural education. Eye-tracking research regarding reading and comprehension in Saudi-Arabia revealed fixation patterns from right to left [61], in contrast to the typical findings in western countries. Li and Briley [62], therefore, differentiate between a habitual eye movement and a situational one, which, on occasions, might be in conflict.

Since the participants for the presented study were all from Germany, we assume homogeneous habituated reading patterns: Since most of their reading materials in everyday life are dextrograde, a gaze movement pattern from left to right and top to bottom was to be expected. One of the most prominent indications for this habituated behavior is visible in the fixations on the answer options at the bottom of the screen moving from left to right on every visualization within this study.

A very similar habitual top-down pattern in the heatmaps is encountered when visualizing the same hierarchy with a treemap (Figure 5), although this visualization does not imply an inherent top-down screen-space structure. Because treemaps do not explicitly follow this structural order with several clearly distinct hierarchy levels, participants might have to reorient repeatedly and remember which elements were already processed. This discrepancy might be partially responsible for the participants' bad performance with treemaps. The same applies to task **T1** where participants again followed a top-down strategy, as illustrated in Figure 6.

Another interesting, but unexpected finding with respect to the treemap visualization was that participants' performance at **T3** with the complex hierarchy was significantly worse than chance level $(t(74) = -4.54, p < 0.001)$. This again indicates that participants were confident in giving a wrong answer. When inspecting the respective heatmap for the whole task processing time (Figure 7), it becomes apparent that fixations concentrate mainly in the upper parts of the relevant regions.

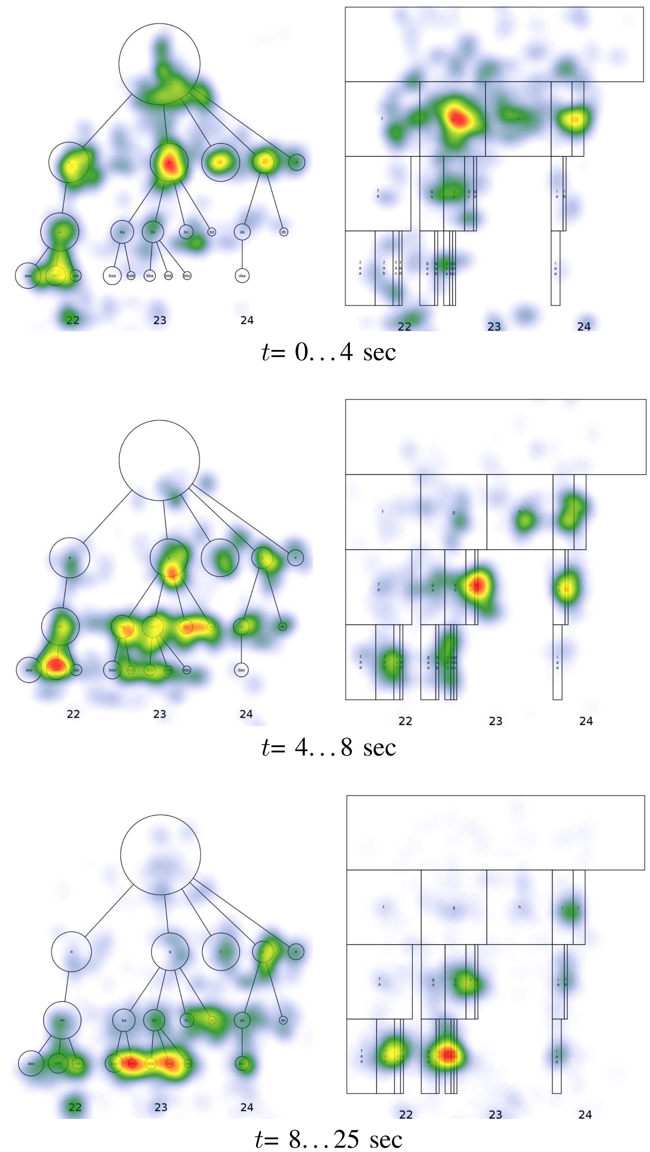


Figure 4. Accumulated heatmaps for the task **T2** and the complex hierarchy for three subsequent periods of time. Note the apparent top-down and left-right pattern of participants' gazes when counting the nodes of the hierarchy.

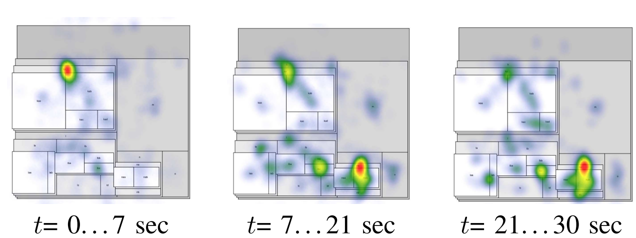


Figure 5. Accumulated heatmaps for the task **T2**, counting all nodes of the hierarchy, and the complex hierarchy. For three subsequent periods of time, we indicate the heatmaps of the treemap visualization. Although treemaps feature only limited top-down characteristics in screen space, the typical European pattern of top-down processing is apparent.

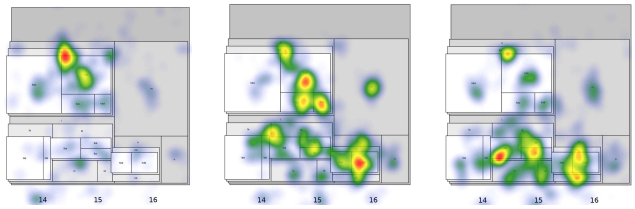


Figure 6. Accumulated heatmaps for the task **T1**, counting all leaves of the hierarchy, and the complex hierarchy. The heatmaps of the treemap visualization are depicted for three subsequent periods of time. Again, the top-down tendency of processing, although the screen space design of the treemap has no such component, is apparent.

Due to the self-occluding design of treemaps, these are the only parts of occluded regions that are directly observable. When only concentrating on the non-occluded parts the areas of nodes l and k are quite equal, although the area of node k is in fact much larger than the area of l. This might have, in combination with the very small area of node o and the relatively large, but mostly occluded area of n, led to the impression that the area of $l+n$ is smaller than the area of $k+o$. Thus, the participants might have followed a misconception of the treemap visualization. The same explanation can account for the significantly lower-than-chance performance of the less complex treemap at **T4** $(t = -2.52;\ p < 0.05)$.

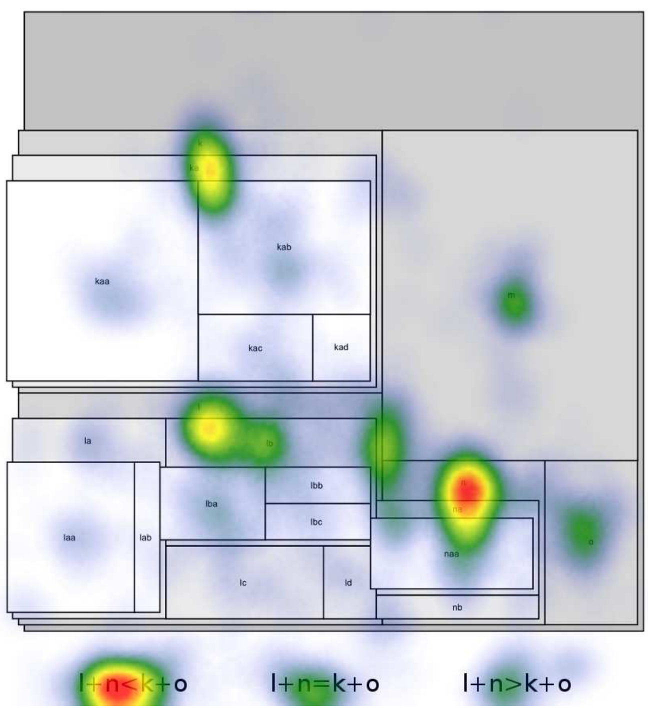


Figure 7. Accumulated heatmap for the whole time of **T3** using the treemap visualization for the complex hierarchy. Participants' fixations concentrated mainly on the upper, non-occluded, parts of the relevant regions, making it hard to correctly estimate the areas.

B. Odds Ratios

In addition to inspecting the heatmaps, we performed statistical analyses for the participants' fixations. When fixations in task-relevant areas of interest are succeeded by task-relevant fixations, the participant's visual attention remains at task-relevant nodes, which is an important feature of effective visualizations. For this, we computed odds ratios, which compare the odds of remaining at task-relevant nodes of two visualizations for each task. We first divided the chance of task-relevant fixations by the chance of irrelevant fixations after looking at relevant areas of interest. This gives us an odd of relevant follow-up fixations for each visualization. We then divided the odds of one visualization by the odds of another visualizations to get the respective odds ratio. This allows to compare two visualizations directly regarding their ability to keep users focused on relevant areas. We used the nodelink visualization as a baseline for the other two visualizations, because it is the most established one. Respective confidence intervals (95%) for the odds ratios allow comparisons of the suitability of a given visualization to promote fixations that remain within task-relevant areas. Odds ratios of around 1.0 indicate that the chance of hitting an important area of interest is not significantly different for both visualizations. Confidence intervals of different visualization combinations not overlapping with 1.0 indicate a significant difference between them. A plot of the different odds ratios and confidence intervals with respect to task and visualization type combinations is given in Figure 8.

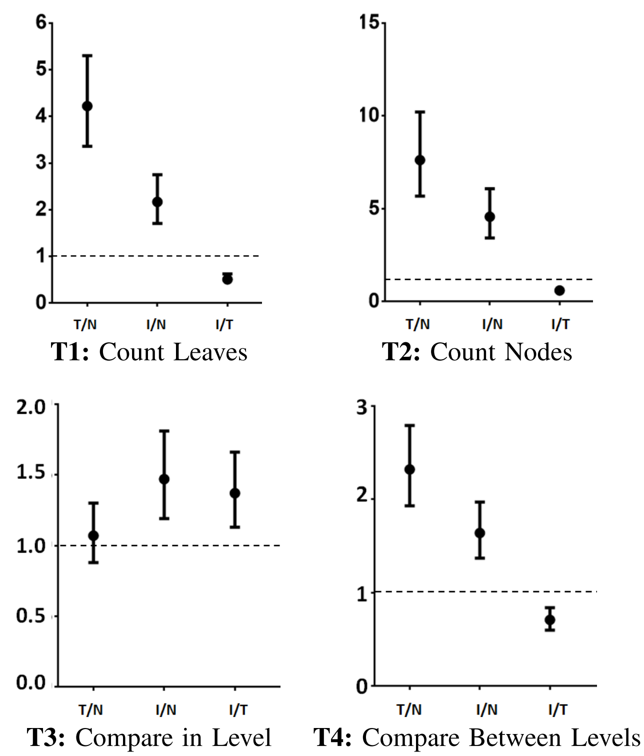


Figure 8. Plots of odds ratios and confidence intervals. For each task and combination of visualizations (N = nodelink, T = treemap, I = icicle plot), the respective odds ratio is indicated together with its 95% confidence interval.

T1 produced significant differences between all visualizations in their ability to draw user attention to task-relevant areas of interest. Within this particular task, the treemap visualization outperforms the other visualizations, regarding its chance to draw attention to task-relevant areas. The odds of looking at important areas of a treemap during the task are four times higher compared to a nodelink ($\Delta\text{odds}_{T/N} = 4.22$; CI: $[3.36, 5.30]$). Comparing icicle plots and treemaps also indi-

TABLE II. DESCRIPTIVE STATISTICS FOR IDENTIFIED PATTERNS. FOR EACH VISUALIZATION WE INDICATE THE NUMBER OF PATTERNS WITH RESPECT TO THE NUMBER OF INVOLVED EVENTS, THE TOTAL NUMBER OF OCCURRED PATTERNS, THE MEAN NUMBER OF OCCURRENCES FOR ALL PATTERNS WITH RESPECTIVE STANDARD DEVIATION, AND MEAN PROPORTION OF THE SESSION TIME IN SECONDS FOR EACH PATTERN WITH RESPECTIVE STANDARD DEVIATION.

Visualization	Number of Patterns According to Complexity			Total Number of Occurred Patterns	Mean Number of Occurrences per Pattern	Mean Proportion of Session Time per Pattern
	2 Events	3 Events	4 Events			
nodelink	7	6	0	1227	94.38 (22.63)	8.46 (5.17)
icicle plot	6	7	1	1643	123.07 (50.70)	5.29 (2.34)
treemap	5	4	0	1099	122.11 (69.61)	3.11 (1.45)

cates a one-to-two advantage for the treemap ($\Delta\text{odds}_{I/T} = 0.51$; CI: $[0.42, 0.63]$). Furthermore, the odds for the icicle-plot visualization are twice as high compared to the nodelink ($\Delta\text{odds}_{I/N} = 2.17$; CI: $[1.71, 2.75]$). These results can be explained by the ratio of relevant to irrelevant screen space, which is highest for the treemap and lowest for nodelink. However, the significant advantage of the icicle plot over the nodelink cannot be explained by the small difference in relevant screen space, but might be a result of the eye-trackers resolution.

T2 presents a similar pattern, but with overall higher odds ratios. The improvement in odds for treemap compared to icicle plot relative to nodelink, however, is only marginally significant. Still, both perform again better than the nodelink in keeping the participants' attention within task-relevant areas. However, when counting nodes, the ratio of relevant screen space to overall screen space is nearly one for the treemap and close to one for the icicle plot. Consequently, participants have only few chances to actually look at non task-relevant positions, directly explaining the very high odds.

The tasks of comparing the volume of two groups of areas **T3** and **T4** reveal rather different odds ratios. Within one level of the hierarchy there is almost no difference between the treemap and the nodelink visualization ($\Delta\text{odds}_{T/N} = 1.07$; CI: $[0.88, 1.3]$), but a slightly higher odds ratio for the icicle plot compared to nodelink ($\Delta\text{odds}_{I/N} = 1.47$; CI: $[1.19, 1.81]$) and the treemap ($\Delta\text{odds}_{I/T} = 1.37$; CI: $[1.13, 1.66]$). When looking at comparisons between different levels of hierarchy, however, both treemap ($\Delta\text{odds}_{T/N} = 2.32$; CI: $[1.93, 2.79]$) and icicle plot ($\Delta\text{odds}_{I/N} = 1.64$; CI: $[1.37, 1.97]$) again outperform the nodelink visualization. Additionally, the treemap is again significantly better than the icicle plot ($\Delta\text{odds}_{I/T} = 0.71$; CI: $[0.6, 0.84]$).

These results suggest that the treemap visualization is indeed effective in promoting task-relevant fixations due to its maximization of screen space. Additionally, the icicle plot performs better in guiding user gaze compared to nodelinks. However, these benefits in visual perception are not reflected in the user performance measure, because nodelinks still perform rather good compared to the visually more efficient visualization techniques. This could be seen as an indicator of the high relevance of previous experience with visualization techniques compared to their visual arrangement. Also, this finding suggests that the sometimes quoted principle of more efficient use of screen space automatically results in higher value of the visualization for the user.

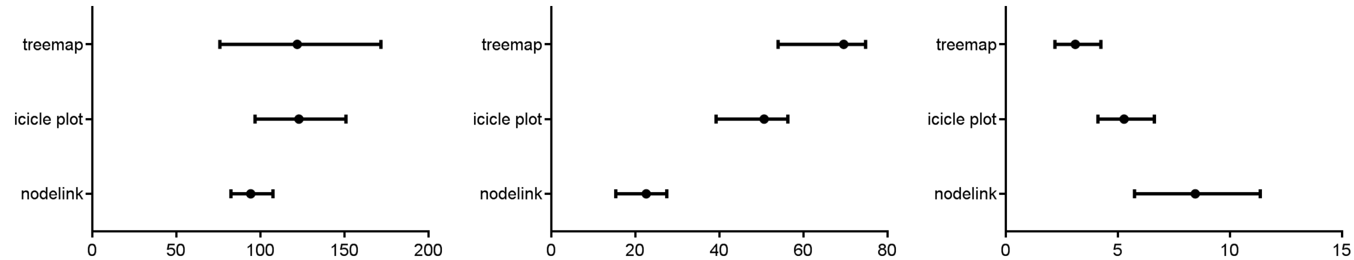
C. Eye-gaze Patterns and Problem Solving Strategies

Another indicator of the visual efficiency of different visualizations is their ability to offer stable problem solving patterns. Following this approach, visually efficient and intuitive visualizations have benefits compared to other visualizations, because of their inherent design. This results in problem solving strategies that are interpersonally invariant. Less intuitive visualizations, however, provoke individualistic problem solving strategies, which highly depend on interpersonal differences and, thus, depend on the user's prior experience rather than intuitive understanding of the visualization. The ability to invoke interpersonally stable gaze patterns can be considered as an indicator of top-down attention allocation due to the visualization's affordances that is closely linked to problem solving, i. e. the user's eyes are guided by the intuitive understanding of the hierarchy's visualization.

In order to investigate, whether nodelinks, icicle plots, and treemaps lead to differences in the employed problem solving strategies, it is necessary to first identify these strategies. Interestingly, empirical research on problem solving only rarely examined behavioral data on a temporal scale. This is also true for eye-tracking data, which are usually analyzed using aggregated data, such as frequencies and durations, of single areas of interest. Because problem solving requires the user to gather information from multiple sources, which then have to be integrated, we added an additional layer into our analysis: Apart from analyzing single areas of interest, we identified repeating patterns of eye movements to investigate the involved problem solving processes.

Automated pattern detection software is able to detect patterns within observations that elude the human eye. To identify problem solving strategies of our participants, we used Theme 6 by PatternVision, which is based on the T-pattern analysis introduced by Magnuson [63] to analyze categorical data on a time scale. A T-pattern is defined by two events happening in significantly similar time intervals. We analyzed the hardest task (**T4**) and ran separate T-pattern analyses on the nodelink, icicle-plot, and treemap visualizations. The pattern search parameters were identical for all three analyses: We only analyzed task-relevant areas of interest to identify only patterns that are relevant to the problem solving process. The criterion for the pattern detection was set to $p < 0.005$ (significance levels for the time intervals) and univariate patterns (follow-up fixations within the same area of interest) were excluded from the analysis. Furthermore, we restricted the analysis to patterns being present in at least 50% of the sample. This way, the T-pattern analysis only identified patterns with a high degree of interpersonal stability. We identified 13 patterns for nodelink, 14 patterns for icicle plot and 9 patterns for treemap. The patterns involved mostly two or three events, only the icicle-plot visualization caused a significant pattern with four events, see Table II.

The identified patterns can be grouped into two categories:



a) Number of Occurrences per Pattern

b) Standard Deviations of the Number of Occurrences

c) Duration of Problem Solving Time in Percent

Figure 9. Bias corrected and bootstrapped 95% confidence intervals for three measures resulting from the pattern detection.

First, across all visualizations participants showed patterns containing nodes whose areas needed to be summed ($n = 17$). Interestingly the majority of these patterns ($n = 14$) involved only the group of nodes that is mentioned second in the task description, but rarely nodes of the other group ($n = 3$). Second, participants showed patterns comparing nodes between the two groups ($n = 19$). Only icicle plot elicited a pattern containing four events. Otherwise, the types of patterns appear to be evenly distributed between the three types of visualizations. Overall we found no evidence for effects of the type of visualization on the number of different pattern types (Fisher's exact test: $\chi^2(4) = 4.20$, n.s.). We also found no significant relation between the type of visualization and the number of identified patterns of different complexities (Fisher's exact test: $\chi^2(4) = 1.85$, n.s.).

To compare the properties of the identified patterns, we analyzed the number of occurrences of the patterns, see Figure 9 a), and the share of time devoted to each pattern between the types of visualization, see Figure 9 c). To test for effects of the type of visualization on both outcomes, we calculated two separate ANOVAs. The ANOVA on the number of occurrences revealed no significant effect of the type of visualization (Brown-Forsythe: $F(2, 16.55) = 1.20$, n.s.). The ANOVA on the share of time devoted to the identified patterns reveals a significant effect of the type of visualization (Brown-Forsythe: $F(2, 18.98) = 7.29, p < 0.01$). Planned contrasts indicate that nodelinks and icicle plots lead to significantly more time devoted to stable patterns compared to treemaps, ($t(1, 24.15) = 7.29$, $p < 0.01$, $\eta^2 = 0.38$). The difference between nodelink and icicle plot was marginally not significant, ($t(1, 16.43) = -2.03$, n.s., $\eta^2 = 0.13$).

The analysis of T-patterns within the eye gaze behavior of participants revealed no significant differences for the types of elicited gaze patterns. This might be a result of the low test power due to the low number of identified patterns. The test power could be raised easily by lowering the criterion of pattern distribution across the samples to a value below 50%, which would reveal a higher number of patterns. However, the resulting patterns would then represent more individualistic approaches to problem solving, which was not our focus of analysis. However, when we analyzed the parameters of the identified patterns, we found that although the number of occurrences of the patterns was not different between the three types of visualization, the standard deviations of the number of occurrences was most homogeneous for nodelinks. This could be interpreted as an indicator of the fact that users are already accustomed to work with nodelinks, because their required number of interpersonally stable pattern fixations is less dependent on the type of pattern than for icicle plot. Both visualizations should elicit patterns with similarly homogeneous occurrences, because both differ only slightly in their representation format and should, therefore, allow similar gaze patterns, yet their gaze pattern occurrences are significantly more heterogeneous.

A significant effect was found for the share of time devoted to the identified patterns. Nodelink and icicle plot elicited patterns with significantly more devoted time than treemap. This is both in line with our analysis of the performance data as well as the analysis of odds ratios to look at relevant elements and with our assumption that intuitive visualizations would produce interindividually stable gaze patterns, which are helpful for the process of problem solving. Overall, our data partially support our findings on the differences of nodelink, icicle plot, and treemap in their visual efficiency. Another approach to analyze identified patterns would be a qualitative comparison between patterns, which, however, is only feasible for more complex patterns, which again would shift the focus of analysis to individualistic problem solving approaches. For example, we identified a significant pattern containing 17 events for icicle plots, but it was only shared by three participants and occurred only once for each of them.

VII. Conclusions and Future Work

We presented a user study, which allowed us to analyze three of the most commonly used visualizations for hierarchical data with additional scalar dimension, namely nodelink, treemap, and icicle plot. These three visualization techniques of two hierarchy complexities (high, low) were tested at four tasks that are common for these types of visualizations. In addition to measuring completion time and correctness of responses, we analyzed the participants eye movements during problem solving. The statistical analysis of the participants' performance revealed that the treemap visualization performed worst. It barely exalted chance level and never performed better than fifty percent. For nodelink and icicle plot, our hypotheses were mostly supported due to well-known properties of both visualizations.

However, we also found some puzzling effects: The analysis of gaze heatmaps revealed that the 2.5D representation format of treemaps was possibly misleading participants during area judgments of occluded nodes. Additionally, we found that the use of icicle plots, with a better screen-space usage compared to nodelinks, might come along with the problem that areas might be judged differently simply because of their mutual distance, i. e., the sum of closely spaced nodes is perceived smaller than nodes with a higher distance. Further, we showed that participants used typical top-down and left-right gaze patterns during the counting tasks, which are better supported by the general structure of nodelinks and icicle plots.

A deeper analysis of the eye-tracking data enabled us to calculate the odds of continued visual attention at relevant nodes. Here, treemaps performed superior in most tasks, which can be seen as proof of its optimized screen-space usage. However, the user performance contradicts this finding: Optimized screen-space usage is no guarantee for good user performance. Interestingly, icicle plots outperformed nodelinks in both comparison tasks with respect to odds ratios, suggesting that icicle plots concentrate participants' attention to the relevant areas by omitting unimportant structures. Moreover, our data revealed that participants devote more time to stable problem solving strategies when using nodelink or icicle plot visualizations. In a future study, one could further investigate the users' problem solving strategies with the help of more complex tasks.

In sum, we were able to replicate several findings from earlier studies, especially about the problematic properties of treemaps. Visualization designers should be aware of the possible misinterpretation of areas of occluded areas. Also the correct identification of the number of inner nodes is often complicated by the occlusion problem. We enriched previous work by recording detailed eye-gaze data, allowing for in-depth inspection and interpretation of the users' processes. Our analyses revealed several pitfalls for visualization design as well as for visual user-study planning and execution, particularly dealing with the powerful Gestalt-laws. Those findings facilitate different directions for future analyses, for example if the choice of nodes' positions plays a crucial role for area perception or if area shape, circular or squared, is a significant factor for good counting, finding, or comparing performance. In general, it seems that classical visualizations are very efficient in most of the practice-oriented cases and that many of the well-known rules of thumb for visualizations have to be investigated much more in the future.

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