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Research article

Leveraging personality as a proxy of perceived transparency in hierarchical visualizations

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ABSTRACT

Understanding which factors affect information visualization transparency continues to be one of the most relevant challenges in current research, especially since trust models how users build on the knowledge and use it. This work extends the current body of research by studying the user's subjective evaluation of the visualization transparency of hierarchical charts through the clarity, coverage, and look and feel dimensions. Additionally, we extend the user profile to better understand whether personality facets manifest a biasing effect on the trust-building process. Our results show that the data encodings do not affect how users perceive visualization transparency while controlling for personality factors. Regarding personality, the propensity to trust affects how they judge the clarity of a hierarchical chart. Our findings provide new insights into the research challenges of measuring trust and understanding the transparency of information visualization. Specifically, we explore how personality factors manifest in this trust-building relationship and user interaction within visualization systems.

1. Introduction

In the context of information visualization (InfoVis), trust is the tendency to rely on visualization and to build knowledge on the information displayed (Mayr et al., 2019). Akin to human relations, the human reader (trustor) can learn to trust or distrust the conveyed information through a subjective evaluation of the quality and reliability of the visualization (Mayr et al., 2019). Furthermore, the trustor judges the visualization (trustee) in terms of its trustworthiness based on its design and delivery properties, e.g., accuracy, objectivity, and completeness of the data (Xiong et al., 2019). Ideally, we want to understand which factors make users engage in "calibrated trust" when interacting with data visualizations, which Elhamdadi et al. (2018) define as the process of *critically evaluating the information, rather than unconditionally dismissing or accepting it*. It is crucial to support visualization designers to create visualizations that elicit trust in the increased use of data visualizations to inform people and make decisions. For instance, the COVID-19 crisis revealed several challenges of spreading information based on how people shifted over time in the trust-building process (Zhang et al., 2022). Although recent research on trust has started to delve into the InfoVis field (see Mayr et al., 2019 for a survey), there is such a small number of studies that the topic offers little empirical data to provide robust guidelines for practitioners. In addition, there is a clear lack of knowledge regarding how individual differences affect the trust-building process (Freitag and Bauer, 2016).

Recently, Crouser et al. (2024) examined how factors endogenous to the visualization (e.g., data source, color, or visualization type) and exogenous factors (e.g., educational background or visualization literacy) affected perceived trust. The authors found that visualization type and visualization literacy were key predictors of trust, and that those relationships were nontrivial. Moreover, the authors state how important it is for future studies to consider other individual factors such as personality to better understand the trust-building and tailor visualizations to different users. Several personality constructs like the Five-Factor Model (FFM) traits (Costa and McCrae, 2008a) may regulate one's trust-building process. For instance, Evans and Revelle (2008) showed that the propensity to trust correlates positively with agreeableness and extraversion and negatively with neuroticism. The authors also found that trustworthiness is positively associated with agreeableness, conscientiousness, and openness to experience scores. Moreover, Chien et al. (2016) also showed that high scores in agreeableness or conscientiousness made individuals trust more in automation processes. Consequently, weighing the bias of personality factors in the propensity to trust can provide a better understanding of visualization transparency assessment.

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In particular, we want to address the effect of personality factors at detailed levels since Alarcon et al. (2018) found that facets are relevant even after controlling for global factors in experimental settings leveraging trust. As such, this work controls for effects from facets of the agreeableness and conscientiousness traits on the perceived visualization transparency. While the former is a dimension that predicts "pro-social and communal orientation toward others from antagonism", the latter suggests "self-use of socially prescribed restraints that facilitate goal completion, following norms and rules and prioritizing tasks" (Costa and McCrae, 2008a). Personality Psychology research has shown that agreeableness predicts trust (Alarcon et al., 2018). Moreover, higher levels of conscientiousness should lead to lower levels of trust based on the propensity of conscientious individuals to be careful and seek to retain control over a situation (Dinesen et al., 2014).

Inspired by these findings, we decided to continue Xiong et al.'s line of work by investigating how the trust-building process can be understood through the scope of visualization transparency (Xiong et al., 2019), defined as *the perceived quality and quantity of intentionally shared information* (Schnackenberg and Tomlinson, 2016). This work presents the results of a repeated measures study where we benchmark three visualizations for hierarchical data against each other regarding perceived transparency while controlling for personality constructs. Research proves differences in visual complexity among different visualizations of hierarchical data structures (e.g., Elmqvist and Fekete, 2009; McNabb and Laramee, 2017; Macquisten et al., 2020). We hypothesize that the visual complexity of the visualizations for hierarchical data may intrinsically connect their processing fluency (i.e., speed and accuracy of perceiving and processing a stimulus). Taking into account that processing fluency is critical to the perception of trust in visual data communication (Elhamdadi et al., 2018), we want to understand if charts for hierarchical data varying in complexity affect how users judge the clarity and effectiveness of the charts in representing the data, and the amount of information they successfully convey. In turn, we expect that these factors will influence how users evaluate the transparency of the visualizations. Furthermore, researchers commonly use visualizations for hierarchical data to understand the manifestation of individual differences in user interaction with visualizations (e.g., Green and Fisher, 2010; Ziemkiewicz et al., 2011, 2013). We analyze our results through the lens of Personality Psychology to understand how personality facets can explain the trust-building process since personality constructs can predict goal-setting behaviors and how individuals interpret information (Hooker and McAdams, 2003). Supplemental materials are available at https://osf.io/n4rk5.

The key contributions of this paper are as follows: First, we identify how the graphical layout trends on perceived transparency in three conventional hierarchical data visualizations while controlling for personality factors. Our set of visualizations, tasks, and datasets does not produce significant changes in perceived visualization transparency. Second, we demonstrate that InfoVis designers can leverage personality dimensions to enhance user characterization and perception modeling in a trust-building process. In particular, the propensity to trust models how individuals judge the perceived clarity of visualization. Future studies are required to understand this relationship more in-depth. Finally, we release the dataset from our experiment.

2. Related work

We present related work to motivate perception evaluation and the trust-building process in information visualization contexts. We also review the state-of-the-art research on the manifestation of personality factors in information visualization.

2.1. Perception evaluation

Stemming from the seminal work of Cleveland and McGill (1984), a large body of knowledge has been expanding in InfoVis regarding how different channels[1] rank against each other as the best approach to depict information by focusing on the accuracy of comparisons and quantitative evaluations made while understanding a plot process (e.g., Vanderplas et al., 2020; McColeman et al., 2021). In particular, these guidelines often focus on mapping task types and graphical channels in a ranking system to guide practitioners in developing their visualizations (McColeman et al., 2021). For instance, we often use bar charts to compare values, line charts to study trends, and scatterplots to estimate correlations (Harrison et al., 2014). Consequently, it is imperative to understand how visual encoding affects human perception and interaction since research shows it affects how fast and accurate individuals are comparing, for instance, means and ranges (Jardine et al., 2020; Ondov et al., 2021).

Other studies looked at how the visualization style influences human perception. The premise is that style influences perception as it is a common approach to making a product stand out (Tractinsky et al., 2000). Research has found that task efficiency improves with the "classical" graphical configuration of visual objects (Salimun et al., 2010) and that the insights that users generate and their interactions depend on the beautification of a visualization (Moere et al., 2012). In addition, meaningful embellishment may also foster cognitive benefits for visualizations (Hullman et al., 2011; Borkin et al., 2015), highlighting it is important to consider the "look and feel" (Lee and Sunder, 2016) in visualization design. For instance, Borgo et al. (2012) focused on the effect of visual embellishments on user perception and cognition. The authors found that using visual embellishments improves information retention at the expense of an increase in processing time.

In this light, one of the fundamental purposes of perception evaluation is to create design guidelines grounded in how people process visual information with their perception and cognitive abilities (Munzner, 2014; Ware, 2019). In particular, these guidelines often focus on mapping task types and graphical channels in a ranking system to guide practitioners in developing their visualizations (McColeman et al., 2021). For instance, we often use bar charts to compare values, line charts to study trends, and scatterplots to estimate correlations (Harrison et al., 2014). Consequently, it is imperative to understand how visual encoding affects human perception and interaction since research shows it affects how fast and accurate individuals are comparing, for instance, means and ranges (Jardine et al., 2020; Ondov et al., 2021). Our work lines with the above findings but focuses on the transparency assessment of hierarchical visualizations with varying graphical dispositions, exploring visual channels that encode quantitative values.

2.2. Trust and visualization transparency

Trust is a multidisciplinary concept based primarily on a social phenomenon (Yan, 2007). In the field of InfoVis, trust remains a challenge since there is limited evidence regarding what might lead a user to trust in visualization without an extensive elaboration of the information (Mayr et al., 2019). There is a strong need to understand the trust-building process with InfoVis because the level of trust in new knowledge generated while users

[1] Channels refer to the properties of a mark, such as size, hue, or position, that can vary, in a chart, to encode the values being represented (Munzner, 2014).

interact with a visualization affects their decision-making process (Sacha et al., 2015). For instance, Dasgupta et al. (2016) evaluated the relationship between the familiarity of the analysis medium and the level of trust of domain experts. Results showed that familiarity with a visualization system inspired trust when considering domain-specific tasks, conventions, and preferences. Furthermore, despite InfoVis helping people recognize patterns and trends in data, trust mediates whether the represented information is used (Kelton et al., 2008). In particular, few studies focus on the cues that convey trustworthiness to users ranging from visualization validity, predictability, or transparency (Kelton et al., 2008; Xiong et al., 2019), to the visual representation of uncertainty (Boukhelifa et al., 2017).

The major limitation of the state-of-the-art research is the lack of reliable and validated methods to assess trust in an InfoVis context (Elhamdadi et al., 2022). Researchers often opt to create Likert scales to measure trust. For instance, Alves et al. (2022) use a single five-point Likert scale to assess trust, while Jian et al. (2000) leverage twelve items with seven points. Besides making it difficult for researchers to iterate on one another and compare experiments, another core issue is the ill-definition of the trust concept in visual data communication research. A lack of a clear definition of trust leads participants to report their interpretation of trust, making it unclear what kind of trust they rate if it is trusting at all (Elhamdadi et al., 2022). Besides the use of proxies, two recent studies tried to define frameworks to consolidate the study of the trust-building process with InfoVis. Elhamdadi et al. (2023) developed VisTrust, a multidimensional conceptualization and operationalization of trust in visualization. The core rationale is that trust can be analyzed through cognitive and affective elements, as well as between visualization and data-specific trust antecedents. In particular, trust in data antecedents considered dimensions such as accuracy, currency, coverage, and clarity. The authors found empirical evidence supporting the framework, in particular reinforcing the role of cognition, affective responses, and individual differences when establishing trust in visualizations. Moreover, Pandey et al. (2023) conducted two experiments to understand the relationships between visual design features and five interrelated facets of trust: credibility, clarity, reliability, familiarity, and confidence. The authors found that colorful visualizations and visual embellishments led to more positive scores, and that factors such as source credibility, content familiarity, and type of visualization affected overall trust rankings. A follow-up study by Crouser et al. (2024) found that visualization type and visualization literacy were key predictors of trust, but those interactions were nontrivial. However, both frameworks are not extensively validated and the authors have already delineated the next steps to create a more robust instrument.

Other researchers rely on perception metrics functioning as proxies of trust. For instance, Elhamdadi et al. (2018) measured the perceived visualization trustworthiness through processing fluency, i.e., the speed and accuracy with which one interprets a visualization. Another relevant work (Xiong et al., 2019) assessed trust through data visualization transparency dimensions (Schnackenberg and Tomlinson, 2016). Xiong et al. (2019) assessed visualization transparency by leveraging the accuracy of the information, the clarity of the communicated information, the amount of information disclosed, and the extent to which the shared information is a thorough representation of the underlying data. Results suggested that ratings of accuracy and disclosure of a visualization predicted ratings of the trustworthiness of that visualization. Dasgupta et al. (2016) also mentioned the increasing role of transparency in explaining trustworthiness. Although all these prospects show promise, there is still the need to continue this research line by defining and modeling trust in visual data communication.

We believe that assessing trust through visualization transparency may provide appealing results in the trust-building process. In our study, we want to understand whether manipulating the presentation of hierarchical data affects how users assess visualization transparency. Previous work has shown that perceived transparency is sensitive to factors such as the amount of data (Xiong et al., 2019) and uncertainty (Jung et al., 2015). For instance, Xiong et al. (2019) found that visualization accuracy and disclosure ratings predicted their trustworthiness ratings. By showing that processing fluency affects the perception of trust in visual data communication, Elhamdadi et al. (2018) also support that visually cluttered charts appear less satisfying and less trustworthy (Sohn, 2017). In other research fields, the state-of-the-art research has increasingly focused on leveraging visualization transparency to understand the use of recommendation systems (Verbert et al., 2013) and remote supervision of collectives (Roundtree et al., 2021), as well as promote better research dissemination overall (Weissgerber et al., 2019). This work builds on the mentioned studies for trust assessment, leveraging visualization transparency dimensions as a predictor of trust with hierarchical visualizations. Moreover, we consider personality profiles in our analysis since individual differences can determine perceived trust (Cacioppo and Petty, 1982).

2.3. Personalty factors

The literature has started to recognize the pitfalls of designing one-size-fits-all visualization interfaces, pushing toward user modeling (Ottley et al., 2015) and adaptive InfoVis systems (Lallé et al., 2019) that leverage personality data to improve user interaction. Among studies addressing the effect of personality in user interaction with InfoVis systems, research often leverages on the Locus of Control (LoC) (Lefcourt, 2014) and FFM (Costa and McCrae, 2008a) traits. The LoC explains how people change because they are continually affected by life experiences. People with an internal LoC believe that the rewards they receive from the environment are explained more likely by their actions. In contrast, subjects with an external LoC attribute the benefits to external entities such as chance. Several studies have shown how LoC is related to search performance across hierarchical (Green and Fisher, 2010), high-dimensional (Delgado et al., 2022), time series (Sheidin et al., 2020), and item comparison (Cashman et al., 2019) visualization designs, visualization use (Ziemkiewicz et al., 2011, 2013), and behavioral patterns (Ottley et al., 2015).

The FFM categorizes personality based on five traits: neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness (John et al., 1999). Research shows that neuroticism and extraversion affect task performance regarding accuracy and completion time (Ziemkiewicz et al., 2013; Oscar et al., 2017; Delgado et al., 2022). Spurious correlations were also less likely to deceive people with high neuroticism scores (Oscar et al., 2017). Moreover, high openness to experience led individuals to be faster while solving problems related to hierarchical visualizations that include conflicting visual and verbal metaphors (Ziemkiewicz and Kosara, 2009). Finally, recent research shows how conscientiousness plays a significant role in visualization-based decision-making (Alves et al., 2023). These studies provide a considerable body of literature on the manifestation of personality facets in information visualization settings (Liu et al., 2020). However, to our knowledge, there is no work leveraging personality traits to understand how it mediates individuals judging the transparency of visualizations or, more broadly, if personality manifests its effects in a trust-building process with visualizations. This research gap offers an opportunity to leverage findings from outside the visualization field and look into the visualization transparency assessment through the scope of personality psychology. For instance, research shows that agreeableness plays a significant role in the trust process (e.g., Freitag and Bauer, 2016; Alarcon et al., 2018). Furthermore, neuroticism and extraversion show prospecting results regarding information transparency (Friberg, 2007). In particular, more emotionally stable individuals need less information transparency, while extroverted people value information transparency the most.

Based on these findings, we expect that personality may also manifest its effects when individuals assess visualization transparency. First, we expect that the agreeableness trait may provide a baseline to analyze how individuals assess visualization transparency since research shows that this trait predicts trust (Alarcon et al., 2018). Agreeableness manifests in the general tendency to be trusting and cooperative with others (Costa and McCrae, 2008a). Second, research has shown that conscientious individuals are transparent and fair (Kalshoven et al., 2011), consistently aiming toward efficiency and outcomes (Ozer and Benet-Martinez, 2006). Dinesen et al. (2014) found that highly conscientious individuals tend to be careful and seek to retain control over a situation, thus trusting less. However, recent human–computer interaction (HCI) research also shows that high conscientiousness scores strengthen the influence of human–computer trust on artificial intelligence acceptance (Huo et al., 2022) and in predictive decision-making regardless of uncertainty (Zhou et al., 2020). In contrast, individuals with lower conscientiousness are more easygoing and prone to going with the flow (Ozer and Benet-Martinez, 2006). Considering our study design, conscientiousness may manifest its effects on the visualization transparency assessment since varying the visual complexity leads to different presentations and organization of graphical elements. Individuals with high conscientiousness scores are typically more sensitive to organizational changes, thus they may also assess visualization transparency differently based on visual complexity. In contrast, individuals with lower scores may disregard the bounding and complexity effects of the design rules for the different visual dispositions and rate each of them similarly. Again, we decided to examine personality in detail and focus at a facet-level.

2.4. Hierarchical data visualizations

Hierarchical visualizations are one of the most common and relevant information structures in computing (Stasko et al., 2000). Researchers have extensively studied visualizations for hierarchical data, specifically focusing on the trade-off between space efficiency and structural clarity (Schulz, 2011). There are two approaches to visually representing this type of data. Node-link diagrams leverage connected nodes with line segments in Euclidean or hyperbolic spaces (Heer and Card, 2004). Although they can offer a clear presentation of the hierarchy, these charts make poor use of the available display space (Johnson and Shneiderman, 1999). The other approach is through space- or radial-filling visualizations (e.g., Scheibel et al., 2020; Macquisten et al., 2022). While space-filling techniques such as the treemap support an overview of large datasets, the implicit encoding of branches makes it hard to understand the hierarchical structure (Johnson and Shneiderman, 1999). In contrast, radial-filling visualizations allow a good understanding of the hierarchical structures with fan-shaped slices but make it hard to compare peripheral elements.

While many types of data exist, we focus on hierarchical data and its corresponding visualizations for two main reasons. First, hierarchical data inherently demands users to interpret both the overall structure and finer details within layers. Past research shows that this data type elicits measurable effects related to individual differences such as personality traits (e.g., Green and Fisher, 2010; Ziemkiewicz et al., 2011, 2013). Given that our study explores personality factors like trust, competence, and deliberation, hierarchical data offers a more complex cognitive challenge, making it pertinent to consider if the visualization complexity of the charts interacts with the personality factors to affect how the stimulus is perceived, e.g., a personality factor is only relevant when we analyze more complex visualizations. Specifically, the need to understand multiple levels in a hierarchical visualization (e.g., in treemaps or sunbursts) encourages users to examine the transparency of the visualization in-depth, which aligns with our goal to study subjective evaluations of transparency.

Second, recent research in the trust-building process with information visualization also leveraged hierarchical visualizations. For instance, Pandey et al. (2023) and Crouser et al. (2024) used the MASSVIS dataset (Borkin et al., 2013), which contains visualizations focused on hierarchical data such as treemaps and Sankey diagrams. This alignment with existing research allows us to extend the investigation into trust and transparency, drawing from proven methodologies. Furthermore, other researchers who are also investigating the trust-building process leverage simpler visualizations such as scatterplots or line and bar charts (e.g., Elhamdadi et al., 2018, 2022), providing useful contrasts to our focus on more complex, layered visualizations.

3. Methodology

This section outlines the methodology used in the experiment to understand *how visual encodings and personality factors affect the visualization transparency assessment*. It starts by describing the study rationale and the research questions, followed by a presentation of the stimuli (visualizations, datasets, and tasks) and the measures collected throughout the experiment. It concludes with the procedure and data analysis techniques used.

3.1. Study rationale and research question

We address this goal by trying to answer our research question: *How does personality mediate the visualization transparency assessment of visualizations for hierarchical data structures?* In this exploratory study, we want to investigate if presenting the same data through different visual channels, e.g., area, angle, or length, affects perceived transparency based on providing easily exchangeable information to enhance comprehensibility and comparability (Roundtree et al., 2019). As we mentioned, visualizations of hierarchical data structures have different visual complexity levels (e.g., Elmqvist and Fekete, 2009; McNabb and Laramee, 2017; Macquisten et al., 2020). Furthermore, Crouser et al. (2024) identified visualization type as a key predictor of trust. We expect that encoding a quantitative variable through techniques with varying visual complexity may affect the processing fluency of the visualization and, consequently, how individuals judge its transparency. However, in contrast with Elhamdadi et al. (2018), we do not intend to reduce the perceived clarity of visualizations by making them harder to interpret. We want to understand if charts for hierarchical data varying in complexity affect how users judge the quality and quantity of the charts and, consequently, trigger how one assesses their transparency.

Previous studies identified relevant visualization transparency dimensions to consider. In particular, three of the most recent works (Xiong et al., 2019; Pandey et al., 2023; Elhamdadi et al., 2023) converge when considering **clarity** and **coverage** as key dimensions in the role of transparency in visualization settings. **Clarity** is defined as the perceived level of comprehensibility of information (Schnackenberg and Tomlinson, 2016), allowing users to read and interpret the visualization. Furthermore, **coverage** refers to the perceived completeness of relevant information (Schnackenberg and Tomlinson, 2016), usually interpreted as "information quantity" in visualizations (Averbukh, 1997). Given the relevance of embellishments and other aesthetical factors in the role of trust in this setting type (Pandey et al., 2023), we opted to analyze the **"look and feel"** of visualizations as transparency proxies as well. The **look and feel** is related to user experience (Costante et al., 2011), focusing on how design factors such as shape, color, style, layout, packaging, and overall visual appearance (Lee and Sunder, 2016) can instill trust and credibility (Fogg et al., 2001; Robins and Holmes, 2008).

Regarding personality, we want to expand the use of individual differences with personality factors to understand their role in mediating the assessment of visualization transparency. From the agreeableness trait, we focus on its trust facet. Costa et al. (1991) define trust as "the tendency to attribute benevolent intent to others". Research shows that this facet predicts the trust-building process by providing a baseline metric (e.g., Alarcon et al., 2018; Mooradian et al., 2006). Since transparency is closely related to trust, we hypothesize that users who score higher in trust may have different expectations of the visualization's ability to convey accurate and transparent information, thus rating the target transparency dimensions (clarity, coverage, and look-and-feel) differently than their peers with lower trust scores. For conscientiousness, we leverage two facets. **Competence** is "the sense that one is capable, sensible, and accomplished" (Costa et al., 1991). Prior work qualifies competence as an individual attribute quality that contributes to human–computer trust (Sousa et al., 2014). We hypothesize that users with higher competence scores may feel more confident in interpreting the visualizations, directly influencing their perception of clarity and coverage. Considering that competence biases how confident one is in their ability to correctly interpret complex visualizations, individuals who are confident in their ability to navigate complex visual information may also experience lower cognitive load, which can positively influence their assessment of how transparent and accessible the visualization appears to them. We also expect that individuals will weigh how and whether they completed the tasks and reflect that appreciation on the visualization transparency assessment. The second facet is **deliberation**, one's tendency to use "caution, planning, and thoughtfulness" (Costa et al., 1991). Psychologists argue that deliberation helps building trust (Asen, 2013), which leads us to believe that it may play a role in the visualization transparency assessment. We consider that, since deliberation reflects the user's carefulness and consideration during decision-making, it will directly impact their subjective evaluation of the visualization's transparency. In particular, we anticipate that users with high deliberation scores may be more likely to scrutinize the visualization thoroughly, thus paying attention to how comprehensively it covers all the hierarchical relationships in the data. Another key aspect is that deliberation may affect how sensitive participants are to the perceived look-and-feel of the visualizations. We expect that users who are more deliberative may consider not just whether the data is clear and fully represented, but also how the design and presentation affect their overall experience of transparency. Consequently, subtle aspects like the ones we are addressing (e.g., the channel used to encode the quantitative data) may influence the subjective perception of transparency.

3.2. Visualizations

We examine three popular hierarchical visualizations: Sankey diagrams, sunbursts, and treemaps (see Fig. 1). Each chart includes visual attributes to encode a quantitative measure that viewers can intuitively compare and understand the data elements. Sankey diagrams encode quantitative values through the length of a bar, and the hierarchical order unfolds from left to right. This chart type usually represents flow between categorical levels to emphasize quantities in a data set. However, we chose this chart as an instance of a tree structure since research has proven its potential to incorporate hierarchy characteristics effectively (Vosough et al., 2018). Sunburst charts use an angle channel to describe quantitative measures. Further, segments of inner circles have a hierarchical relationship with segments of the outer one, which lies within the angular sweep of the parent segment. Finally, treemaps leverage nested rectangles whose area is proportional to a quantitative variable to depict a tree structure. Sunbursts and treemaps are among the most common layouts to visualize large amounts of data (Gorodov and Gubarev, 2013).

Our visualization choices allow us to understand how people reason about the prevalence of fixed quantities while following a hierarchical structure (Shneiderman and Wattenberg, 2001; Stasko and Zhang, 2000). Furthermore, the channels of each chart type allow us to manipulate the perceived fluency of each chart regarding how cluttered they are Bertini and Santucci (2006). While we designed each chart on a 750×750 pixel canvas, the presentation of the hierarchy varies between them. More specifically, the graphical elements in the Sankey are well-spaced between hierarchy levels, and the user has to follow flow lines to navigate between those levels. Although this graphical configuration fosters intra-level analysis due to the y-axis alignment, it complicates comparing the size of two elements between hierarchy levels. Moreover, while the sunburst and the treemap are space-filling presentations, the treemap has an overlap of marks which leads to occlusion. In contrast, the sunburst has no occlusion, leading participants to perceive the treemap as more challenging to interpret. We believe that the different encodings of the visual marks in each chart are enough to trigger variations in perceived visualization transparency when individuals are reasoning about the presented information. We developed the dashboard[2] using HTML5, CSS, and Javascript. In particular, the charts were created with the `D3` library.[3] We use monochrome grayscales to minimize biases from user preferences and color semantics. In addition, it is color-blind safe. We checked through a pilot study ($N = 3$) that participants could understand the font size of the labels and the different categories by color.

3.3. Datasets

To control for knowledge and preference biases, we created three datasets to show in each visualization. The three datasets are based on the same underlying data structure to create visualizations that differed only in the labeling (i.e., renaming data variables, adjusting titles, and updating legends to reflect the specific context of each dataset). It means that they have the exact same hierarchical structure and the same quantitative values associated with each leaf. Consequently, the structure of the data remained the same across the different topics to maintain consistency when comparing the results of different visualizations. This approach allowed us to test how users' evaluations of visualization transparency were influenced by the presentation of the data, not by structural differences between datasets or biases. For instance, people may be biased by preferences if the dataset leverages music genres or food types. As such, we use three different themes to diminish the learning effect of the domain over the experiment. Moreover, using a specific topic for

2 Available at https://web.tecnico.ulisboa.pt/~tomas.alves/phd/Apparatus/Alves2022_Hierarchy-Vis.zip (Last access: 29/Nov/2023).

3 https://d3js.org/ (Last access: 29/Nov/2023).

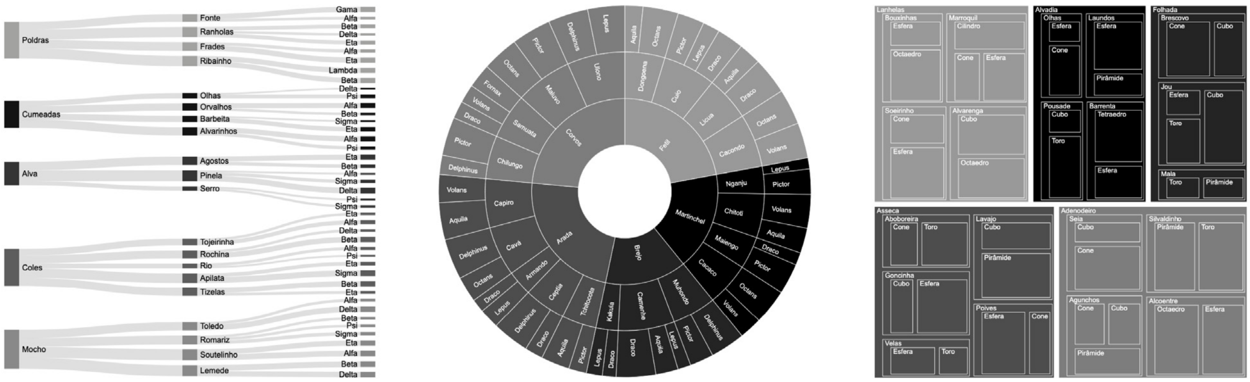


Fig. 1. Three charts of the same hierarchical dataset but with different graphical layout. From left to right: Sankey diagram, sunburst, and treemap.

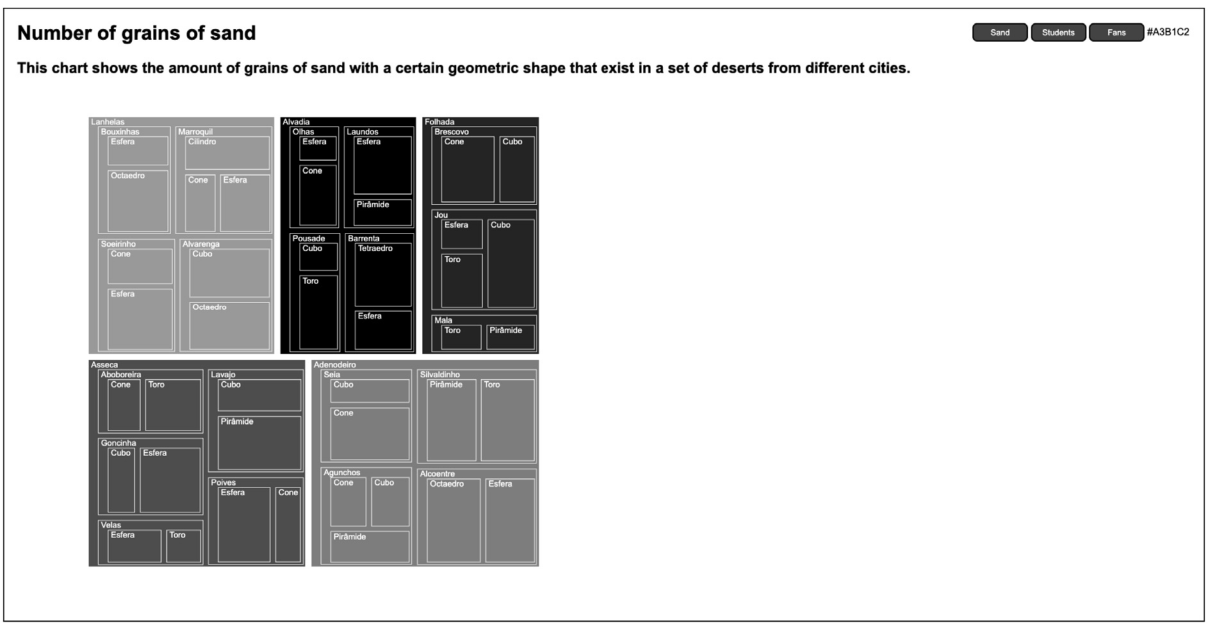


Fig. 2. Example of a screen with the visualization and the description of the domain in our experiment. The title, the description, and the buttons to change the domain were translated from the native language to English.

each visualization allows us to guarantee across all participants that the answers for the tasks can focus on the same target independently of the visualization. Above each visualization was a title corresponding to the context (see Fig. 2). The three possible contexts were: (i) *Fans*, which presented the number of fans per band acting at music festivals hosted in different cities; (ii) *Sand*, which shows the number of grains of sand of a particular shape present in deserts from different cities; and (iii) *Students*, which includes the number of students per faculty of a university from different cities.

We chose this labeling approach to avoid a learning bias or potential perceptual and semantic confounds. In particular, we use the names of actual small villages to refer to cities, concerts, deserts, and universities. Shapes of grain are labeled based on geometrical 3D shapes, faculties on Greek letters, and, finally, music bands on star constellations. Each domain has three hierarchy levels, henceforth referred to as *upper*, *middle*, and *lower*. In addition, the quantitative measure of each domain is its *domain unit*. For instance, the *Fans* domain depicts the number of fans as a *domain unit* with the bands as the *lower*-level category, the music festivals as *middle*-level categories, and *upper*-level categories are cities.

3.4. Tasks

We evaluated five tasks for each visualization: hierarchy fragmentation, between-level analysis, maxima identification, sum estimation, and value retrieval. There was only one instance for a domain for each task type, resulting in a total of 15 tasks (5 types $\times$ 3 domains). We framed each task using plain language as follows:

Hierarchy fragmentation *Which category has the most subcategories?*

Between-levels analysis *Which city has the <middle level> with the largest number of <lower level instance>?*

Maxima identification *Which is the <lower level> with the largest number of <domain unit> from <middle level instance>?*

Sum estimation *How many <domain unit> are there in <upper level instance>?*

Value retrieval *How many <domain unit> are there in <lower level instance> from <middle level instance>?*

Hierarchy fragmentation required participants to find the category with the most subcategories. Between-levels analysis asked participants to assess which group from the *upper*-level had the highest value from a specific *lower*-level instance. While maxima identification prompted participants to report the highest value from the *lower* level of a fixed middle-level category, sum estimation asked subjects to estimate the quantity of a fixed *upper* hierarchy instance. Finally, retrieve value tasks required finding the value of a specific item in the visualization from the *lower* level.

We chose the tasks based on other research studies that ask participants to interact with visualizations for hierarchical data (e.g., Müller et al., 2017; Ziemkiewicz et al., 2013). Our choices cover a wide range of task types achievable using each chart type. In particular, these low-level goal tasks are part of the most primitive analysis task types in visual analytics (VA). We employ them not to instill trust directly but to promote a careful analysis of the hierarchy structure and how the channels represent data. In particular, tasks took the form of questions we expected participants to consult the visualization to answer. Consequently, we expect that completing the tasks will be enough to take in and understand the nature of the graphical representation and trigger variations of the visualization transparency assessment. Even though exploratory tasks may allow these phenomena, we opted to focus on questions that had a single correct measure to be able to track when the assignment ended.

Regarding past work that used similar task types (e.g., Green and Fisher, 2010; Ziemkiewicz et al., 2011, 2013), the authors asked participants to "identify a target located somewhere within the presented informational hierarchy", which is similar to our "Sum estimation" and "Value retrieval" task types since they require finding a specific item. Those works also asked inferential questions, which were more open-ended, asking the participant to find a specific classification and then find another classification in another part of the taxonomy that had something in common with the first. Both our "Between-levels analysis" and "Maxima identification" task types required participants to inspect the visualization, finding a specific visualization through comparisons. Like past work, our task types represent simple data lookups and more complex analytical tasks. However, they are simplified versions of typical visual analytical tasks focused on higher-level cognitive processes. Participants had no time limit to complete the tasks, and we accepted only one response to each question.

3.5. Measures

We use questionnaire-based metrics to have a better understanding of how the graphical presentation of hierarchical data and personality affect the trust-building process:

Personality scores We collected personality data with the Revised NEO Personality Inventory (NEO PI-R) (Costa and McCrae, 2008b; Lima and Simões, 2000), as it allows researchers to assess the FFM five personality traits and their 30 facets. We calculate responses by the sum of the Likert Scale based on assertions semantically connected to behaviors and five possible alternatives of agreement: *strongly agree*, *agree*, *undecided*, *disagree*, and *strongly disagree*. Overall, the questionnaire has 240 items, including 30 different subscales (one for each facet), with eight items for each subscale. Although it is an extensive questionnaire, it is the shortest version of an FFM measurement apparatus that provides scores for facets. We obtained the scores for the trust, competence, and deliberation facets through this instrument. High scores exacerbate the characteristics of the facets, and vice-versa, i.e., higher scores in the competence subscale mean that individuals have a higher disposition to be more capable and accomplished.

Visualization transparency As we mentioned, we examine transparency through three dimensions: clarity, coverage, and "look and feel". Participants rated their agreement to one statement about each aspect of transparency through a five-point Likert scale ranging from *I disagree* (1) to *I agree* (5). The statements for clarity, coverage, and look and feel were *"I think this visual representation allows me to compare categories correctly"*, *"I think this visual representation shows the information with an appropriate level of detail"*, and *"I think this is the best design to visualize hierarchical information"*, respectively.

Demographics We recorded the gender, age, and self-reported visual acuity of each participant, as well as whether they were color-blind through a simplified version of Ishihara tests (de Alwis and Kon, 1992). Moreover, we presented to the participant an instance of each chart we use with an exemplary domain, which is different from the ones we designed for the experiment (see Section 3.3). Then, we asked participants to (i) assess their familiarity with that visual representation in a five-point Likert scale ranging from *not familiar* (1) to *very familiar* (5), (ii) report the name of the chart, and (iii) to respond to an analysis question similar to the ones used in the study (see Section 3.4) to assure whether participants could understand the information the visualization conveyed independently of their self-assessed familiarity.

3.6. Procedure

We recruited 51 participants (26 females, 25 males) aged 20 – 61 ($M = 28.31$, $SD = 11.02$). We recruited participants through standard convenience sampling procedures such as direct contact and word of mouth. Due to constraints from COVID-19, we conducted each user test as a Zoom video meeting with one experimenter. Users participated remotely in a location of their choosing. We asked them to be in a room without noise or other distractions that might affect their ability to pay attention to the procedure. Moreover, we informed participants that we would record the screen, which type of data would be collected, and that they could quit the experiment at any time.

The study consisted of four phases: (i) demographic questionnaire, (ii) tutorial, (iii) formal study, and (iv) visualization transparency questionnaire. This division assures that the assistant follows the necessary steps in each test and promotes homogeneity between the experiments. We separated the demographic questionnaire into two parts. The first part included all demographic and personality data except visualization literacy. Participants completed the first part of the questionnaire before the experiment on their own time given the effort needed to fill in the questionnaire. We administered the second part after presenting the study to each participant in the experimental session. All participants reported having normal or corrected-to-normal visual acuity and not being color-blind. We continued by introducing a tutorial to the charts, including their name and how they should interpret information regarding hierarchy and quantitative semantics.

The formal study consisted of three blocks, one per pair of visualization type and domain. The order by which a participant interacted with a pair ($visualization$, $domain$) was assigned randomly before the experiment in each instance, i.e., first, we randomly ordered the three visualization options, then the contexts, and paired by their index in the order. As such, the pairs included mutually exclusive instances of visualization and domain, e.g., one experiment consisted of the order {($sunburst$, $fans$), ($sankey$, $students$), ($treemap$, $sand$)}. Subjects had to complete five different tasks in each block (see Section 3.4) without time constraints. The order by which a subject performed the tasks was based on a Latin squares distribution to reduce order effects. After

Table 1
Descriptive statistics of unadjusted and adjusted metrics means and variability for each visualization type with the personality facets as covariates. Covariates appearing in the model are evaluated at the following values: Trust = 19.71, Competence = 22.29, Deliberation = 20.24. Note: M = Mean, SD = Standard deviation, SE = Standard error. Cell color encodes the rank between chart types across the dependent variables: green (maximum), yellow (in-between), and red (minimum).

		Visualization		
		Clarity	*Coverage*	*Look and Feel*
Unadjusted (M±SD)	Sankey	3.49 ± 1.17	3.43 ± 1.23	3.65 ± 1.13
	Sunburst	3.96 ± 0.96	3.80 ± 0.94	3.75 ± 1.06
	Treemap	3.29 ± 1.15	3.37 ± 1.02	3.04 ± 1.26
Adjusted (M±SE)	Sankey	3.49 ± 0.17	3.43 ± 0.18	3.65 ± 0.16
	Sunburst	3.96 ± 0.14	3.80 ± 0.13	3.75 ± 0.15
	Treemap	3.29 ± 0.15	3.37 ± 0.13	3.04 ± 0.18

Table 2
ANCOVA results for each visualization transparency dimension with the personality facets as covariates. Covariates appearing in the model are evaluated at the following values: Trust = 19.71, Competence = 22.29, Deliberation = 20.24. Note: ":" represents an interaction effect. Bold text represents tests with statistically significant results.

	Visualization transparency dimension		
	Clarity	*Coverage*	*Look and feel*
Encoding	$F(2, 94) = .437, p = .647$	$F(2, 94) = 1.704, p = .188$	$F(2, 94) = 1.142, p = .324$
Trust	$F(1, 47) = 1.851, p = .180$	$F(1, 47) = 3.030, p = .088$	$F(1, 47) = 0.090, p = .765$
Encoding : Trust	$\mathbf{F(2, 94) = 3.473, p = .035}$	$F(2, 94) = 1.977, p = .144$	$F(2, 94) = 0.121, p = .886$
Competence	$F(1, 47) = 0.467, p = .498$	$F(1, 47) = 0.917, p = .343$	$F(1, 47) = 0.024, p = .877$
Encoding : Competence	$F(2, 94) = 1.220, p = .300$	$F(2, 94) = 0.195, p = .823$	$F(2, 94) = 0.645, p = .527$
Deliberation	$F(1, 47) = 0.033, p = .857$	$F(1, 47) = 0.140, p = .710$	$F(1, 47) = 0.060, p = .807$
Encoding : Deliberation	$F(2, 94) = 0.245, p = .783$	$F(2, 94) = 0.907, p = .407$	$F(2, 94) = 0.286, p = .752$

completing the three blocks, we asked participants to assess the dimensions from visualization transparency for each visualization (see Section 3.5). Subjects had access to all scales simultaneously to reduce the anchoring bias. After completing the questionnaire, participants received compensation for their time.

3.7. Data analysis

We used one-way repeated measures ANCOVAs to investigate the main effect of the visualization layout in each visualization transparency dimension score. To understand whether individual differences act as confounding factors, we use personality scores (competence, deliberation, and trust) as covariates. For the ANCOVAs, we tested for sphericity (Mauchly's test) and used the Greenhouse–Geisser correction when the assumption was not met. We complement our analysis through Spearman's correlation tests. In particular, we verified whether the metrics from personality, familiarity, and visualization transparency were correlated intraclass. We include LOESS (locally estimated scatterplot smoothing) lines to help analyze the correlations with minimal assumptions about the relationships among variables (Friedman and Stuetzle, 1982). LOESS lines attempt to capture general patterns in relationships while reducing the noise by fitting a polynomial surface determined by one or more numerical predictors using local fitting.

We ran an apriori power analysis using the `pwr` R library[4] to determine the minimum sample size required to test the study hypotheses. Results showed the required sample size to achieve 80% power for detecting a medium effect (0.3) with a significance criterion of $\alpha = .001$ was N = 53 for multiple regression methods. With a sample size of 51 participants, we believe the obtained sample size is adequate to test the study hypotheses. Furthermore, the central limit theorem implies that our sample size supports using ANCOVAs even if the original variables themselves are not normally distributed without major problems (Pallant, 2020).

4. Results

This section covers the results of our study. It tackles the relationship between visualization transparency and personality. We present data as mean ± standard deviation unless otherwise stated. Fig. 3 and Table 1 provide an overview of the descriptive statistics. Table 2 shows the main and interaction effects of the ANCOVAs. Fig. 4 shows the coefficients of the Spearman's rank-order correlation tests for each chart.

4.1. Clarity

Participants rated the sunburst higher in clarity ($3.96 \pm .958$) compared to the Sankey (3.49 ± 1.173) and the treemap charts (3.29 ± 1.154). However, it appears that there is no main effect of the visualization on the perceived clarity, whilst controlling for all personality variables. We found that the trust facet alone significantly interacts with the visualization layout on the clarity assessment with a medium effect size (partial $\eta^2 = .069$). It appears that this relationship depends on the graphical presentation of the data since the trust covariate did not show a significant main effect. Fig. 5 shows how the trust facet positively influences how individuals judge the perceived clarity of the treemap ($p = .018$). There were similar but nonsignificant trends for the sunburst ($p = .646$) and an opposite one for the Sankey ($p = .849$).

In contrast, the conscientiousness facets appear to have no effect on how participants assess the perceived clarity. It appears that individual with average competence tend to assess perceived clarity with higher scores in the sunburst ($p = .236$) and the

[4] https://cran.r-project.org/web/packages/pwr/vignettes/pwr-vignette.html (Last access: D:20250222).

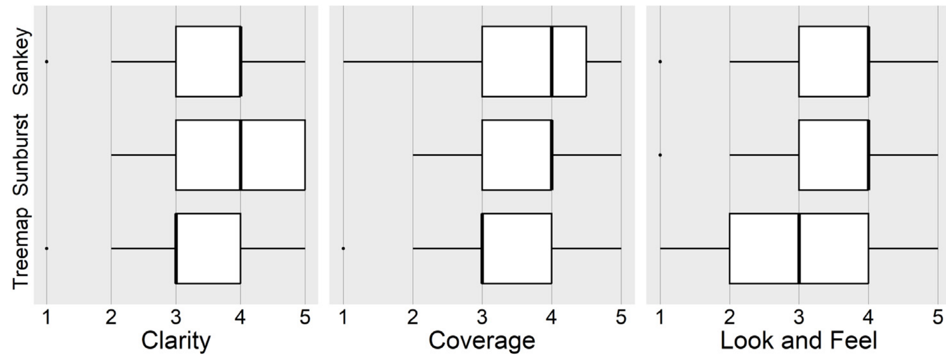
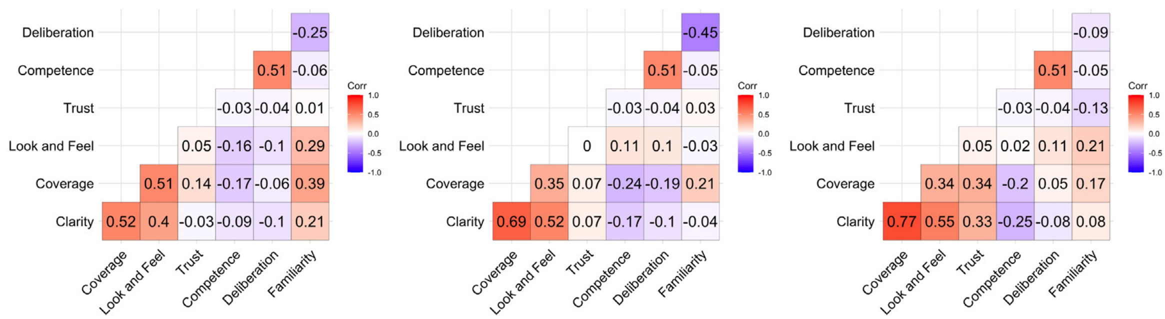


Fig. 3. Unadjusted quantitative results of the experiment per visualization type and metric.



(a) Sankey. (b) Sunburst. (c) Treemap.

Fig. 4. Spearman correlation coefficient matrices of trust assessment and demographic factors in the different visualizations.

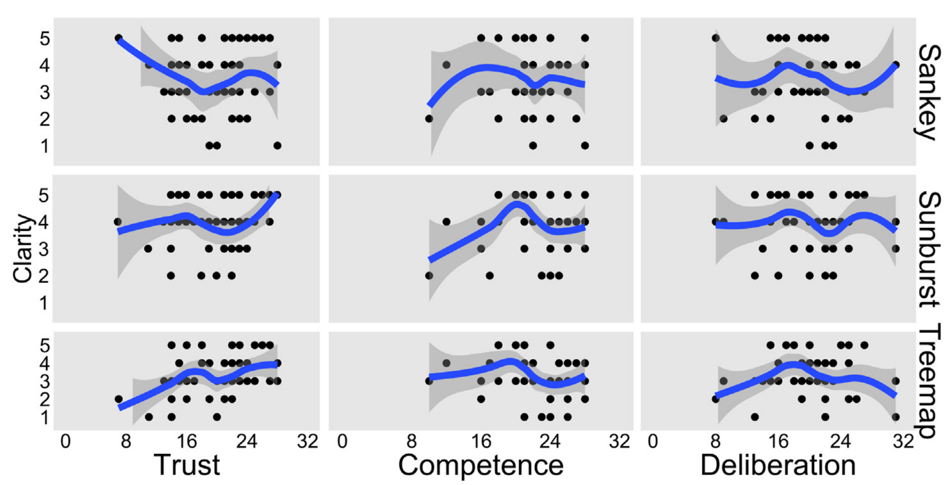


Fig. 5. Scatterplots of perceived clarity per visualization and personality facet scores.

treemap ($p = .072$). For the Sankey, people tend to keep similar scores independently of the competence facet ($p = .549$). Finally, results show that individuals with average deliberation scores attribute higher perceived clarity to the treemap than the remaining people ($p = .580$). In contrast, the Sankey ($p = .469$) and the sunburst ($p = .490$) produce several u-shaped trends.

4.2. Coverage

There was also no statistically significant difference in perceived coverage based on the visualization layout while controlling for all personality scores. Results show that subjects provided higher scores in coverage for the sunburst ($3.80 \pm .939$), followed by the Sankey (3.43 ± 1.285), and then the treemap charts (3.37 ± 1.019). Regarding personality, the trust facet does not significantly affect the perceived coverage of a chart. However, there is a positive trend in the treemap ($p = .015$). We also found a trend from individuals with average to high trust scores reporting higher perceived coverage for the Sankey ($p = .310$). In contrast, these individuals assess the sunburst with lower scores ($p = .603$).

Similar to the perceived clarity, we found that neither the competence nor deliberation scores affect the coverage assessment of hierarchical visualizations (Fig. 6). Interestingly, there were also trends from individuals with average competence scores assessing with higher coverage the sunburst ($p = .092$) and the treemap ($p = .159$). In contrast, those with lower trust

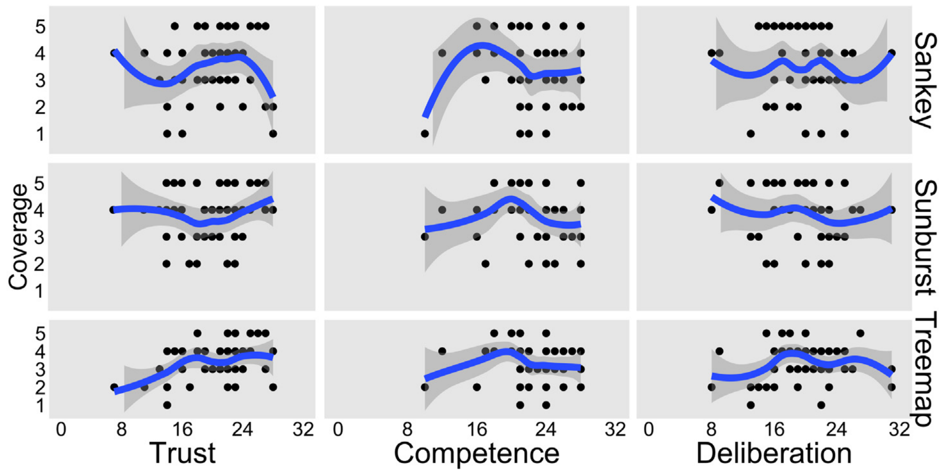


Fig. 6. Scatterplots of perceived coverage per visualization and personality facet scores.

scores believe that the Sankey diagram has more coverage ($p =$ .239). Deliberation also appears to trend with the visualization type regarding how individuals judge the coverage dimension. In particular, there are several u-shaped trends in the Sankey ($p = .683$), sunburst ($p = .191$), and treemap ($p = .704$) charts.

4.3. Look and feel

The treemap received the lowest scores ($3.04 \pm .958$), compared to the remaining charts. While the Sankey obtained scores of 3.65 ± 1.128 points, participants rated the sunburst with 3.75 ± 1.055. An ANCOVA showed no significant differences across the different layouts on perceived look and feel while controlling for all personality scores. Although the trends suggest that participants assess that the design of the Sankey and the sunburst charts is better than the treemap when visualizing with hierarchical data, these differences are not statistically significant.

The trust, competence, and deliberation facets appear to not play a role in how participants assess the look and feel dimension. A closer inspection of Fig. 7 shows that the influence of personality facets on the look and feel assessment is weak. Contrary to the past dimensions, trust appears to not affect how individuals assessed the treemap ($p = .746$). The distributions in the Sankey ($p = .738$) and sunburst ($p = .983$) charts also reassemble a null effect. For competence, the Sankey ($p = .253$) and the sunburst ($p = .444$) distributions are almost mirrored. However, the relationship between competence and perceived look and feel is almost inexistent in the treemap ($p = .911$). We can see similar distributions can be seen for the deliberation facet. Again, the Sankey ($p = .475$) and the sunburst ($p = .506$) distributions appear to mirror one another. Finally, the distribution hints that individuals with average deliberation scores assess with a slightly higher look and feel the treemap than their counterparts ($p =$ .431).

4.4. Additional findings

We decided to analyze also whether the self-reported familiarity with the layouts affected the results. First, subjects reported a positive familiarity with the sunburst chart ($M = 4.18, SD = .68$), followed by the Sankey ($M = 3.86, SD = .92$), and then the treemap ($M = 2.90, SD = 1.28$). However, participants were not accurate in naming the charts (Sankey: 9.80%, sunburst: 1.96%, treemap: 17.65%). They answered the tasks with high accuracy rates (Sankey: 90.20%, sunburst: 100%, treemap: 100%). Therefore, we believe that participants had the minimal level of knowledge necessary to perform the experiment tasks. Interestingly, only the Sankey chart reported significant two-tailed correlations between visualization trustworthiness dimensions and self-reported literacy. In particular, we observed that the self-reported literacy affected the coverage ($p = .005$) and the look and feel ($p = .037$) of the Sankey diagram.

Regarding the educational background, our sample is composed of individuals with secondary education (19.6%), a bachelor's degree (45.1%), a master's degree (29.4%), and a doctoral degree (5.9%). We ran one-way ANOVAs with a Bonferroni correction to understand if the background affected the dependent variables. We did not find any significant results. Therefore, we believe that the background did not play a relevant role in the study. Spearman correlation coefficients show that each visualization transparency dimension significantly correlates with the other two for all visualization layouts, with medium to large effect sizes (Fig. 4). It suggests that participants were consistent while rating the transparency dimensions of the visualizations.

We continued our analysis by assessing the visual clutter of the tested idioms. Similar to recent research in InfoVis (e.g., Flittner and Gabbard, 2021; Locoro et al., 2023; Kunkel and Ziegler, 2023), we measured the visual clutter through the feature congestion algorithm developed by Rosenholtz et al. (2007). The algorithm runs on arbitrary images (Rosenholtz and Jin, 2005), and its analogy is that the more cluttered a display is, the more difficult it is to introduce a visually salient object. We ran the algorithm using an image containing only the visual marks for each chart on a white background, as depicted in Fig. 1. The feature congestion algorithm scores the clutter in a local part of a display through the local variability in color, orientation, and luminance contrast as features. Scores greater than four indicate more cluttered arrangements (Rosenholtz et al., 2007). The Sankey (4.7463) and sunburst (4.9120) charts showed similar scores. In contrast, the treemap reached the highest feature congestion score (6.4460). The results align with our expectations since cluttered images can become a barrier to cognitive processing (Rosenholtz et al., 2007). This trend may explain why participants rated with similar values visualization transparency dimensions of the Sankey and the sunburst while assessing the treemap with poorer scores.

5. Discussion

Conventional design knowledge in visualization often neglects the trust-building process when users interact with information visualization. We anticipate that leveraging visualization transparency opens a rich design space for innovation of visual communication to promote how people trust in science

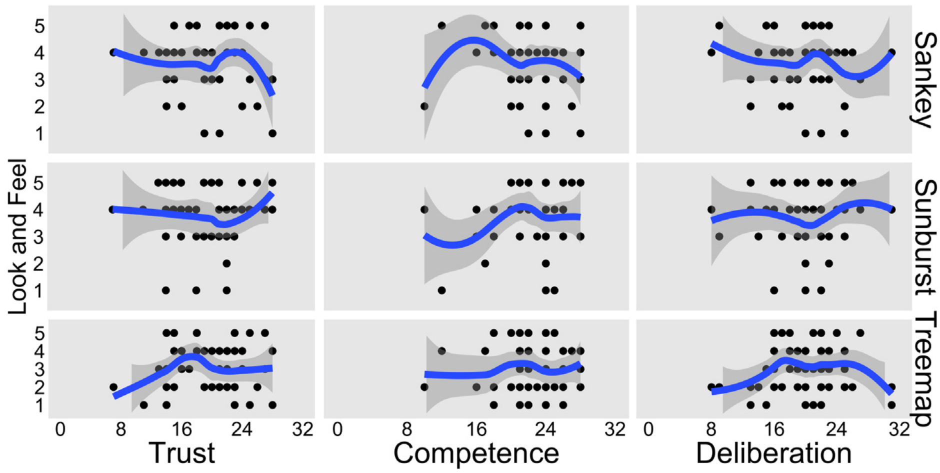


Fig. 7. Scatterplots of perceived look and feel per visualization and personality facet scores.

findings (Sacha et al., 2015). Instead of solely maximizing the data-to-ink ratio, designers may wish to inflate the transparency of the visualization, prompting users to build their decisions on the information displayed (Mayr et al., 2019). To contribute to this research field, we conducted a user study where participants have to interpret data and gauge the visualization transparency of hierarchical graphs with different visual channels to encode quantitative variables. Past studies show that these visual channels lead to different accuracy, response time, or bias rates (McColeman et al., 2021). In particular, users are better at assessing quantity elements using length and angle visual channels than with areas (Vanderplas et al., 2020). Our work focuses on three hierarchical charts that use these visual channels: the Sankey diagram encodes quantities with length, the sunburst with angles, and the treemap with areas. We found no significant effect of the graphical presentation on the visualization transparency assessment while controlling for the personality facets. However, the descriptive statistics of the self-assessment metrics follow the trend in human perception studies. In particular, participants rated with similar values the visualization transparency dimensions of the Sankey and the sunburst while assessing the treemap with poorer scores. In this case, higher scores mean more perceived transparency.

This finding provides an initial understanding of how users perceive the transparency of the visual channel cues. While, in this case, participants could accurately complete all tasks independently of the visual channels, we observed that individuals do not assess them equally. We focused on choosing tasks that made participants "read" the visualization, thus prompting an assessment of their perceived readability (Cabouat et al., 2024). However, it is possible that the tasks participants performed were not cognitively demanding enough to highlight differences in transparency assessment across different visual channels. In this case, participants may have relied more on their prior knowledge rather than the visual cues of the different visualization types, reducing the impact of the visual channel differences. Although the cognitive load needed to assess transparency might not have been high enough to evoke significant distinctions across visual channels, our work is in line with previous work from Kosara (2019b), reinforcing that individuals perceive limitations in treemaps for proportional comparisons. Another reason may be that perceived transparency may inherently be a subjective measure that does not align perfectly with objective qualities of visual channels. For instance, perceived transparency may depend on other factors outside the specific visual channel used, such as context, data familiarity, or the perceived complexity of the chart. Kosara (2019a) support this theory when they found that the perceptual cues are perceived as more or less relevant by users when they analyze the charts, even when the data is the same. In our case, results hint toward users reporting a higher level of transparency for visualizations that they are familiar with, aligning with the relationship between visualization literacy and trust found by Crouser et al. (2024).

We were also able to observe that personality appeared to play a role in the trust-building process. Results show that the trust facet significantly interacts with the visualization layout when individuals judge its clarity, but it is only evident in the treemap. This medium-size positive effect suggests that one's baseline tendency to trust in others can bias the perceived clarity of graphical layouts, even when the hierarchical and quantitative structures are the same. In particular, people who score high on trust may interpret the design of treemaps more favorably because they are less skeptical of the visualization's structure and may not be as focused on its inherent limitations, such as the difficulty in comparing areas. Therefore, those with high trust scores may rely on their predisposition to believe in the accuracy and clarity of the visualization presented than the cognitive effort for accurate interpretation. Although we did not measure trust explicitly through Likert scales, our finding indicates that the propensity to trust according to the FFM manifests its effects in a visualization context. These results are in line with past psychology research (e.g., Freitag and Bauer, 2016; Alarcon et al., 2018) and, consequently, we believe that the trust facet can help understand the trust measurement.

The trust-building synergies of conscientiousness that occur in real-life social settings do not directly transfer to the assessment of visualizations. We found no significant effect from the conscientiousness facets on perceived clarity. Regarding perceived coverage, results suggest that the trust facet produces a nonsignificant, medium size trend on perceived coverage. Again, this trend is more evident when participants interact with the treemap. Results also suggest that the competence facet may negatively influence the perceived coverage of each chart with weak to moderate nonsignificant trends. These trends may derive from the individuals with a strong sense of competence being more likely to critique the implicit encoding of hierarchy in space-filling charts, where area or angle makes it harder to assess relationships. Nevertheless, we hypothesize that the visual complexity of the charts was not distinctive enough to produce measurable effects of the conscientiousness' facets. Another reason may be that the highly structured and well-designed visualization tasks may not significantly interact with conscientiousness facets since the charts already offer structure and order. Therefore, conscientiousness may not play a significant role because the stimuli already align with the personality trait's tendencies. However, the trends open up future opportunities to understand better the role of conscientiousness in visualization settings.

Finally, the look and feel dimension appears to be independent of personality. The lack of significant results regarding the look and feel assessment may be related to conscientiousness and its facets being the least emotionally charged of the FFM (Shiota et al., 2006). We aimed to understand whether presentation of the data items would be assessed differently based on the personality profile given the disparate predispositions towards being more sensitive (competence) or prone to plan (deliberation). As we found no results, future studies may consider including other factors in the personality profiles, e.g., openness to experience (Costa and McCrae, 2008b), since it measures interest in aesthetics, among others.

6. Limitations & future work

While the above recommendations provide preliminary insight into visualization transparency and its susceptibility to personality factors, there are some limitations to the results of this study. First, we focus on the perception of visualization transparency dimensions, which are not directly observable or measurable (Hopkins, 1998). Moreover, we applied self-developed scales since there are no established measurement scales (Elhamdadi et al., 2022). As such, issues such as wording (Loftus and Zanni, 1975) or the number of points on a Likert scale (Juniper, 2009) may introduce noise in the measurement of visualization transparency. We followed the five-point scale approach of Xiong et al. (2019) to diminish this external effect. Future work should focus on replicating the findings of this study and verifying whether they transfer to other types of charts.

Second, we consider that the study sample was adequate to analyze the variations of clarity, coverage, and look and feel assessments. However, latent variables such as personality traits often require hundreds of participants to achieve stable estimation (Kretzschmar and Gignac, 2019). Future work should aim at recruiting a significant number of participants to verify whether our results hold for larger samples. In addition, other personality variables such as openness to experience and its facets should be present while studying visualization transparency. Third, the tasks we designed allowed participants to compare between and within hierarchical levels, highlighting the differences in granularity of the elements. Consequently, the tasks may focus more on visual analytical behaviors than how users are likely to review a tree structure. Future work should explore more task types, especially matching task type and perceived transparency dimension to gain a broader picture of transparency. High-level decision-making tasks to tackle sensemaking (Dimara and Stasko, 2021) and real-work and in-context case studies are also relevant. The context of our datasets may have also affected the validity of the transparency assessment. While Xiong et al. (2019) used firefighters as a scenario where trust in the validity of maps plays an important role, identifying the number of fans, shapes of sand, or students in universities may not trigger the trust-building process with the participants. Another appealing factor to investigate in future studies is how perceived accuracy affects the trust-building process. Researchers can use datasets with a familiar domain or provide tutorials before the interaction.

Since the entire chart environment and graphical presentation often affect chart perception, future studies should also include changing other factors, e.g., chart size, scale, or color palette. For instance, all three studied charts might have included labels on internal nodes indicating the number of child nodes to support the quantitative tasks. Moreover, the monochrome grayscale to encode categorical data may have biased participants in their assessments. Future work should also explore other design approaches to encode this type of data, embellishment factors (Moere et al., 2012), and interactivity features. Furthermore, the relationship between the encoding channel and the chart type should be explored more in-depth. For instance, future work can fix the chart type and investigate if the encoding channel is the only factor affecting the trust-building process or if it interacts with the chart type. Another example is the visualization ordering aspect which may affect how well users perceive the information it conveys. While the ordering in a y-axis with the Sankey helps interpret the chart, it becomes harder to understand the order in sunburst (Chen et al., 2015) and treemap layouts (Shneiderman and Wattenberg, 2001). We encourage future work to study these potential factors since the visual clutter metrics (Bertini and Santucci, 2006) may act as a confounding factor in the measurement of visualization transparency.

Finally, our work suggests that some personality profiles may assess their perceived trust for visualizations with higher scores or which visual layouts individuals prefer to see in their systems, among others. On the one hand, we imagine that in scenarios such as the COVID-19 pandemic, research can leverage these findings for the public good. Recent research shows that different visualizations of the same COVID-19 data can affect how individuals interpret information (Padilla et al., 2022). For instance, at the beginning of the pandemic, it was typical for a news outlet to present visualizations to the public to showcase the evolution of hospitalizations and the daily virus propagation. In this case, fostering the public trust in the visualizations could benefit the population by making them acknowledge and process the information presented to them. Moreover, it could lead to enforced house confinement behaviors and, consequently, diminish the incidence of COVID-19 infection cases. On the other hand, research on human factors can also be applied unethically. For instance, knowing which visual encodings or personality factors affect one's trust-building process can be exploited to spread misinformation. Designers with such intents can pass information to the general public with a chart assessed with better transparency dimensions by individuals. Although we do not discard that an individual may question the information and disregard it, it is not the same for every individual. Consequently, people who typically avoid questioning what is being presented to them may acknowledge and miss a critical reflection on the information, leading them to trust it. Indeed, the COVID-19 crisis revealed several challenges of spreading information based on how people shifted over time in the trust-building process (Zhang et al., 2022). In this light, our work focused on identifying whether and which personality profiles manifest their effects in the trust-building process. We advise that our findings should be used following ethical guidelines to design visualizations. The supervision of visualization content is out of the scope of this study, yet we hope that future research can develop filters to find malign use of information visualization.

7. Conclusions

This work continues the research line of understanding trust in InfoVis (Mayr et al., 2019) and takes one of the first steps to evaluate how the visual presentation of hierarchical data affects the perception of visualization transparency while controlling for personality factors. Results show that the trust facet plays a role in the evaluation of a graph's clarity. Additionally, the initial results from the competence and deliberation facets suggest that more work is needed to understand the dynamics produced in the trust-building process. Making visualizations more trustworthy and cognitively in line with the personality characteristics of users will not only help scientific findings to be more empowered in public trust but reveal new guidelines and designs for personality-aware visualization decision support systems. We believe that the inclusion of these factors in visualization should exploit the advantages of intelligent technologies to design visualizations that empower people with diverse abilities, supporting the vital role that decision-making has in society (Dimara and Stasko, 2021).

Ethical approval

This study was reviewed and approved by The Ethics Committee of Instituto Superior Técnico. The reference number for this approval is 22/2021 (CE-IST).

CRediT authorship contribution statement

Tomás Alves: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Carlota Dias:** Investigation, Methodology. **Daniel Gonçalves:** Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing. **Sandra Gama:** Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

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

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