A Change of Perspective: How User Orientation Influences the Perception of Physicalizations

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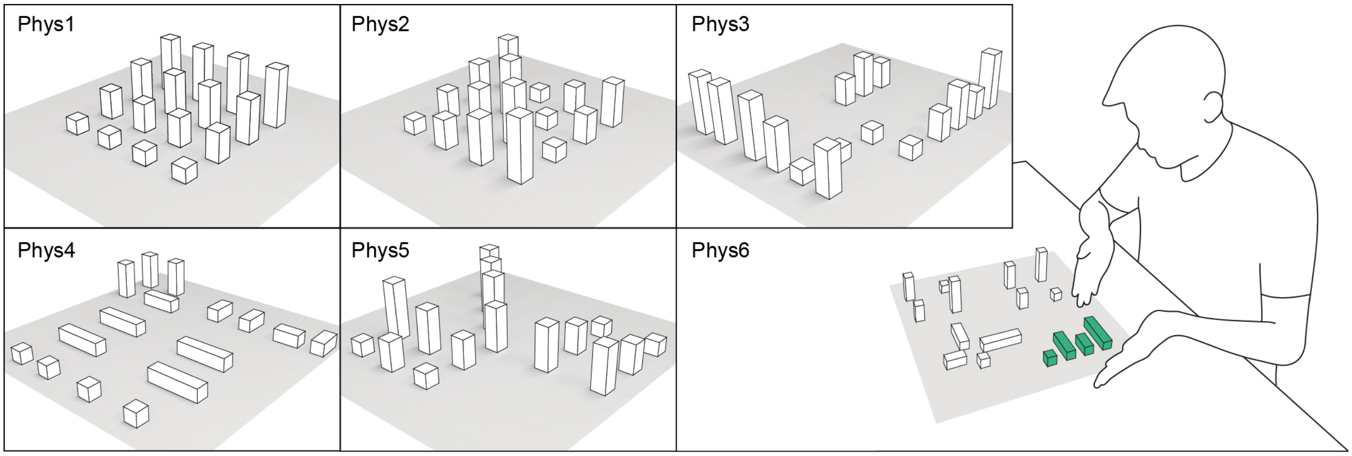

Figure 1. The 6 exemplar physicalizations (Phys1 – Phys6) and a depiction of the experiment setup. The physicalizations were presented to participants from 4 different orientations according to the vertices of the plane. Participants completed 3 tasks including clustering, filtering and finding the extremum in the abstract 'data'.

ABSTRACT
As physicalizations encode data in their physical 3D form, the orientation in which the user is viewing the physicalization may impact the way the information is perceived. However, this relation between user orientation and perception of physical properties is not well understood or studied. To investigate this relation, we conducted an experimental study with 20 participants who viewed 6 exemplars of physicalizations from 4 different perspectives. Our findings show that perception is directly influenced by user orientation as it affects (i) the number and type of clusters, (ii) anomalies and (iii) extreme values identified within a physicalization. Our results highlight the complexity and variability of the relation between user orientation and perception of physicalizations.

Author Keywords
Data Physicalization; Physical Visualization; User Orientation.

CSS Concepts
• **Human-centered computing ~ Human computer interaction (HCI)**; User studies; Visualization;

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INTRODUCTION
Physicalizations are *"physical artifacts whose geometry or material properties encode data"* [15]. As a consequence of their physical three-dimensional nature, information retrieval is sensitive to angle and perspective changes of the user. For example, factors such as occlusion, depth perception and height estimation in physical space can prevent the user from effectively extracting information. Moreover, what happens when different people observe the same physicalization from a different side or perspectives?

Although some prior work acknowledges the possibility of perspective being an influence on how physical information is perceived [24], *no prior studies actively consider the relation between user orientation and perception.* The focus is often on individual interaction from a single position, which might originate from interactions as we know them with 2D visualizations. Examples include collaborative settings in which users are limited to one viewing angle, or physicalizations in which accompanying interfaces, labels, or legend are placed in a particular direction, which biases the viewing angle [8,9,24]. This single-perspective approach conflicts with the argument that physicalizations foster collaboration and allow for interactions around them [15], which works on the assumption that physicalizations effectively communicate data in all directions, and to all users equally.

However, we argue that this assumption should be investigated as the consequences can be problematic for data interpretation and make physicalizations ambiguous. If people perceive a singular data physicalization differently from different perspectives, they will interpret the data in different ways. Therefore, a systematic and principled approach to understand how the orientation of an individual influences their perception of data is needed. This allows us to derive empirical insights that can guide the design of physicalizations that take observation from multiple perspectives into account.

To examine the relation between orientation and physical information communication, we conducted an experiment with 6 exemplar physicalizations and presented them from 4 different perspectives to evaluate information retrieval across perspectives. The design of the 6 physicalizations is informed by prior work into physical 3D bar charts [6,9,10,23]. Our study with 20 participants evaluates the influence of users' orientation on how they perceived the physicalizations during multiple tasks.

Our results indicate that orientation directly impacts perception, leading to strong inconsistencies in the way the physicalization communicates information. We contribute: (i) a confirmation of the relation between user orientation and the perception of physicalizations, and (ii) provide a first characterization of the variability and complexity within this relation. In this paper, we elaborate on the study rationale, the designed physicalizations and describe the conducted study. Finally, we will present and discuss the findings and provide recommendations for future work.

BACKGROUND

Physicalizations

Physicalizations are *"physical artifacts whose geometry or material properties encode data"* [15] and have several benefits over conventional visualizations. They make data physical and allow for tangible exploration and interaction. There are promising findings on the effectiveness of data physicalizations for information retrieval and how active touch facilitates this, in comparison to on-screen 3D visualizations [14].

Physicalizations come in many different forms that go beyond information retrieval. For example, *data sculptures* [28] aim to communicate data in a more artistic form or *casual information visualization* [18] which examines the everyday use of data for reflection or social behaviors [22,25]. Others have focused on re-configurable physicalizations, either within the interaction possibilities of a fixed grid of physical bars [10,24] or even *constructive visualizations* [12], allowing the user to be their own curator of data [11,13, 16]. Differing from static physicalizations, shape-changing interfaces [1,19] are dynamic objects which display real-time data. One aim of shape-changing interfaces is to use physical qualities to enhance people's interaction with digital data [19], similarly to physicalizations. Examples of work in which shape-changing properties are intertwined with physicalizations are LOOP [20], Relief [17] and inFORM [10].

The challenges of user orientation

Although a large body of work exists within the field of physicalization, the influence of user orientation on physical properties has so far *not been actively studied*. User orientation is a general problem across fields, for example in holo-displays and tabletop systems. However, these systems are based on visualizations with an inherent 2D character, whereas physicalizations make use of tangible 3D objects, which extend the area from a plane in space [7].

Most related work does not actively consider that physicalizations could be perceived differently from different angles and/or perspectives. This is exemplified in physicalizations that come with a complementary digital interface placed on one side of the system [8], indicating people to interact with it from a single side. Another empirical example is that many of the users' creations on ShapeCanvas [9] were dependent on the reading direction and user orientation, such as names, facial expressions, symbols and a game simulation using 'up and down'. In contrast, some prior work does acknowledge the possibility of perspective being of influence on perception but provide no further characterizations. For example, in EMERGE [24] the 3D nature of the system allows people to observe it from different perspectives which can help to confirm relations in the data. Lastly, CairnFORM [5] is a prototypical 360-degree readable, physical ring chart to increase readability of data from multiple angles in public spaces.

Insight from other fields

Looking at prior findings from psychophysics [21] we can only make presumptions about the perception of physical objects in general. For example, the early work from Baird [4], shows the complexities of the perception of size and distance. Another example is the radial-tangential illusion [3], illustrating that lengths presented away from and towards the body are perceived to be larger than lengths that are presented from side to side to the user. This indicates that the perceived length of an object depends on its orientation. Lastly, research has also considered the way people construct spatial relationships [3] and whether these are constructed by object to object comparison or self to object comparison. However, much of this prior work uses drawings rather than actual physical 3D objects and in the few studies using actual physical stimuli, participants' heads were usually fixed [4].

Summary and implications

The consequences of the lack of understanding of the relation between user orientation and perception are profound as people might interpret data differently depending on what side of the physicalization they are viewing. This could impact collaboration and create discrepancies between people leading to incorrect interpretations. To summarize, when viewed from different perspectives, none of the studies on physicalizations take user orientation into active consideration and therefore its relation to perception remains unclear. Additional work is needed to characterize this relation and provide guidelines on how to build physicalizations utilizing the full potential of physical space in conveying information.

STUDY RATIONALE

By studying the relation between user orientation and data perception we can examine to what extent physicalizations become ambiguous when viewed from different perspectives. Ambiguity is problematic as an important incentive for data physicalization is to effectively communicate information through physical properties. For example in EMERGE [24], all participants moved between at least two sides of the system and performed different movements such as head tilting and leaning over the top during the study. It was however unclear if these movements were performed to counteract occlusion or were strategies for reading the data more accurately. A central question is: *how can we develop a better understanding of the relation between user orientation and perception of physicalizations?* Our work aims to address this question by examining (i) how people perceive data from different perspectives and (ii) how the perception differs across perspectives and/or people.

We propose a systematic approach to investigating the complex relation between user orientation and perception of 3D physicalizations. For this study, we define orientation as the *user's perspective view of the physicalization*. We acknowledge that user perception is not only susceptible to rotation in the plane, but also for example by angular view, which is a conjunction of the user's height and the height of the physicalization. However, we study orientation as a first step in developing a better understanding of user perspective on perception of data physicalizations. By examining different information retrieval tasks across orientations, we can draw conclusions about the consistency of perception across these tasks. We propose ***orientation consistency*** as new terminology for a measure of *the consistency of user responses to information retrieval tasks across different orientations*.

In order to measure *orientation consistency* for exemplars of physicalizations, we applied information retrieval tasks known from 2D visualizations [2,27]. Specifically, we focus on familiar concepts in data interpretation such as *clustering* similar elements, *filtering* for a particular condition and *finding* the *extremum* within the given data set [2].

METHOD

The goal of our study is to investigate the impact of 90-degree changes in orientation on the perception of bar chart physicalizations. We hypothesize that orientation directly influences the perception of the physicalization and results in discrepancies and ambiguity in the way data is interpreted. For this study we rotate exemplars of physicalizations by 90 degrees on a flat plane, resulting in 4 orientation conditions. More specifically, we want to understand the relation between orientation and perception on three different layers: (i) per **physicalization**, (ii) per **participant** and (iii) for different types of **information retrieval tasks** (clustering, finding anomalies and extremum). We focus in this study on static representations of data to keep the number of factors and the duration of the experiment under control.

Design

We choose a set of 6 physicalizations as they represent a range of complexity that provides enough depth to compare different information retrieval tasks. Figure 1 shows all 6 physicalizations and in the remainder of the paper we refer to them as '*phys1-6*'. Each of the 6 physicalizations consists of 16 blue acrylic objects: 4 cubes of 20mm and 12 cuboids with 4 of each length: 40, 60 and 80mm. The shape of the objects is derived from the well-known static physical bar charts often used for physicalization [6]. We explicitly chose not to include indicators of data mapping, to avoid recognition bias in the study. Therefore, the physicalizations are not explicitly based on an underlying dataset, but rely on intrinsic and relational properties of the objects in line with the definition of physicalizations. We choose to use 16 objects for each physicalization and vary them in 4 lengths, to achieve approximately the same density, while keeping simple numerosity to facilitate pre-attentive processing [26]. The layouts of the 6 physicalizations were created by applying different physical properties informed by what is known in 2D visualization as pre-attentive visual properties [26]. We elaborate on each of these properties below:

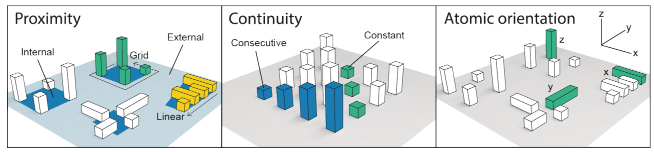

Figure 2. Illustration of different physicalization properties, which were changed across the exemplar physicalizations.

Property 1 – Proximity

"Spatial proximity is one of the most powerful perceptual organizing principles and one of the most useful in design" [26]. Things that are closer are perceptually clustered together. In our designs, proximity was used to create differences in internal and external distances between objects on the 2D plane. For example, in phys1 and phys2 internal proximity is constant, visually creating one cluster. Whereas in phys6 internal distance is smaller than external distance, resulting in the objects most-likely being perceived as 4 clusters (Figure 2). Additionally, proximity was used to make two different types of spatial relations, either in a grid or linear fashion (in horizontal, vertical or diagonal direction).

Property 2 – Continuity

Continuity assumes connectedness and can, in this instance, occur by height or orientation. In our study, continuity by height was either created by using objects of similar size or placing objects of increasing size in a consecutive manner. This respectively results in *constant* or *consecutive* continuity (Figure 2). Continuity in orientation is realized by aligning seemingly separate objects to form a single line or shape.

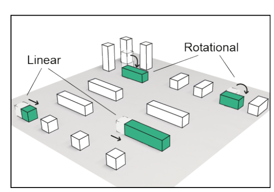

Figure 3. Phys4 contained deliberate errors in atomic orientation of one object in each cluster, if clustered on proximity and orientation.

Property 3 – Atomic orientation

Atomic orientation refers to the individual orientation of the cubes/cuboids in the physicalization, in the x, y or z plane (Figure 2). 4 of the physicalizations have only upright oriented objects and 2 have mixed orientations, with phys4 containing a deliberate error in the orientation of one object per cluster (Figure 3).

For the purpose of our study, we intentionally created physicalizations containing edge cases of the different properties, resulting in the different aspects possibly opposing each other. For example, in phys1 (Figure 4), according to the *proximity* between objects or their *orientation* it is 1 cluster (1C), however assessing them by *continuity* it results in either 4 clusters of objects of constant sizes (4 clusters type 1 or in other words 4C-T1) or 4 clusters of objects of consecutive sizes (4 clusters type 2 or 4C-T2).

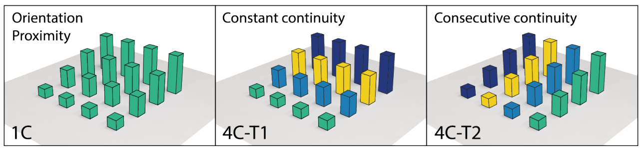

Figure 4. Phys1 cluster formation for (i) proximity or orientation, (ii) constant continuity or (iii) consecutive continuity.

Setup

The working area is a white fixed square canvas of 40x40cm to not reveal changes in orientation. Above the table was a camera providing a top down view of the participants' gestures and interactions with the physicalizations (Figure 5). We presented each physicalization from 4 orientations - *North, East, South, West* (Figure 6) - to cover the major viewing angles. The 24 tasks were randomized using the Latin square method to avoid learning effects due to specific layouts. While the participants finished the task, the researcher would build the successive task with a second set of objects.

Participants

We recruited 20 participants (9 identified as female, 11 as male) with an average age of 27 years (σ = 5.92). The only prerequisite for eligibility was that participants are fully (or corrected to fully) sighted as we were interested in visual perception of physical compositions that could represent data.

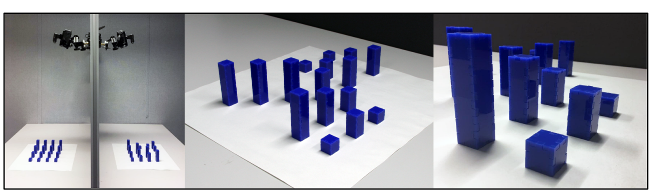

Figure 5. Experiment setup and a close-up of the acrylic objects.

Procedure

At the start of the study we provided an introduction, participants signed a consent form and we collected demographics. We explained the goal of the study: to understand how people observe physical objects that represent (abstract) data. We gave participants a set of general instructions and one example task was performed to make them familiar with the tasks and procedures. We instructed the participants to look at the physicalization from a fixed position and to not move their head. We did not constrain participants in their physical movements, allowing slight natural movement. However, they were not allowed to lean down, move around, or touch the physicalization, therefore their movements did not fundamentally change their perspective. We provided them with the definition of a cluster: *a set of objects that you think belong together; it is not about the atomic properties of each object, but about their relation to each other.*

During the study, participants were consecutively presented with 24 different physicalizations, the 6 physicalizations each seen from the 4 orientations. To make the concepts of 'data clustering, finding anomalies and extremum' accessible, we used the terminology 'identifying groups, standouts and highest and/or lowest values'. For each of the 24 physicalizations, the same set of information retrieval tasks were performed (Figure 6), the following 3 questions were asked:

Question 1: Can you identify any groups of objects? To capture which object relations the participant observed, we asked them to identify any clusters of objects they perceived. We asked them to point out the clusters with their hands to capture the exact location and structure of each cluster.

Question 2: What is the group that stood out first to you? To capture the anomalous cluster of objects that initially drew attention, we asked the participant to point out which cluster they saw first. In this way we could collect both the absolute location and the structure of the anomalous cluster, given that they answered at least one to the previous question.

Question 3: Can you point out the highest and lowest value(s)? To capture the perceived extremum (minimum and maximum), we asked the participant to point out what they perceived as one or more lowest and highest values. We omitted any reference to size being indicative of high or low values and left it open to participants' own interpretation.

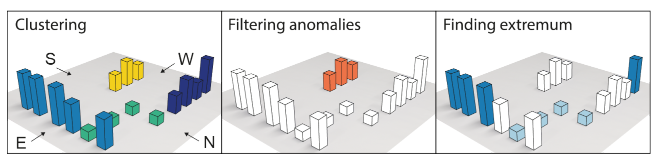

Figure 6. Illustration of the 3 information retrieval tasks for each physicalization and from each of their orientations.

We captured the answers to these questions on worksheets with visual representations of the physicalizations which allowed for the annotation of the location and composition of clusters, anomalies and extremum. Ambiguity in capturing user selection was avoided through researcher clarification with the participant. Each physicalization task took approximately 5 minutes, which made the whole experiment last between 90 and 120 minutes, depending on the participant.

Data collection & analysis

We recorded top-down video of the tabletop and the hands of the participants. Additionally, the feedback of the participants was audio recorded. Lastly, the researcher made notes of the feedback during the experiment. During analysis these worksheets were cross referenced with video footage of the whole interaction. We applied a coding scheme to capture all *occurrences* of (i) identified number and type of clusters, (ii) anomalies and (iii) extremum per orientation as well as across the 4 orientations. Moreover, we created a visual library to capture the clustering, filtering and finding extremum process of each participant. These were visual representations of each occurrence to capture the high-fidelity information of abstract interpretations of the physicalizations, e.g. *number* and *type* of clusters (Figure 7).

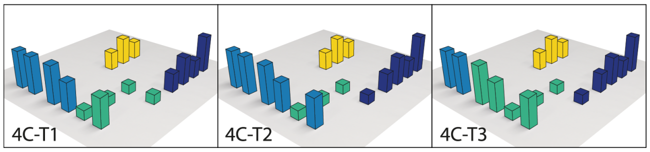

Figure 7. 3 types of clusters each containing 4 distinct clustering of objects identified for phys3. For each, #C refers to the number of clusters and T# refers to the specific type of clustering.

To analyze the impact of orientation on the 3 different information retrieval tasks, we compared the 4 orientations of each physicalization for *each task* and for *each participant*. This comparison was to measure the consistency of a participant's perception of a physicalization across all 4 orientations. We refer to the 4 orientations as *North, East, South* and *West.* To categorize participants' consistency and to facilitate our comparison, we assigned a value, the *orientation consistency* (OC) as shown in Table 1.

OC-VALUE	ELABORATION	ORIENTATION CONSISTENCY
OC-1	Four distinct orientations	1/4
OC-2	Two identical orientations	2/4
OC-3	Three identical orientations	3/4
OC-4	Four identical orientations	4/4

Table 1. OC-values for categorizing participants' consistency in a physicalization, across its orientations, for a given task.

For example, a participant with OC-2 for a physicalization means that they completed an information retrieval task consistently across 2/4 orientations. This means that they observed the data similarly for only 2 out of 4 orientations. Likewise, if a participant completed an information retrieval task inconsistently across all orientations, i.e. 1/4, they would have a value of OC-1. This means there was no consistency in the way they observed the data across orientations.

Using this OC-value, we categorized 3 information retrieval tasks over a total of 6 physicalizations and 20 participants resulting in 360 *instances* (3x6x20). One *instance* encompasses all 4 orientations (N, E, S, W) and has an assigned OC-value that represents one task completed by one participant for one physicalization.

Finally, in the case of OC-2, i.e. a participant completed a task consistently across only 2 orientations, the orientations can be either adjacent (ADJ) or opposite (OPP) to each other. Considering this, we made the following subdivision:

(i) Identical adjacent orientations (e.g. N,E)

(ii) Identical opposite orientations (e.g. N,S)

(iii) 2 pairs of identical adjacent orientations (e.g. N,E - S,W)

(iv) 2 pairs of identical opposite orientations (N,S - E,W)

FINDINGS

Overall orientation consistency

We report the general *orientation consistency* of the perception of clusters, anomalies and extremum across physicalizations and participants. If orientation did *not* affect the perception of the physicalizations, 100% of the *instances* would be identical across all 4 orientations. Table 2 shows that for ***clusters***: 37% of the instances were identical across all 4 orientations, 27% were identical across 3 orientations, 33% across 2 orientations (20% were adjacent) and 3% were distinct across all 4 orientations. For ***anomalies***: 19% of the instances were identical across 4 orientations, 15% were identical across 3 orientations, 54% across 2 orientations (36% were opposite) and 13% were distinct across all 4 orientations. Lastly, for the ***extremum***: 29% of the instances were identical across 4 orientations, 21% were identical across 3 orientations, 23% across 2 orientations (17% were adjacent) and 28% were distinct across all 4 orientations.

This data confirms our hypothesis that perspective directly influences the user's perception of physical information, showing that across all tasks, participants, and physicalizations there is a *systematic lack of consistency* and perspective directly influences users' perception of physical information.

TASK	4 IDENTICAL	3 IDENTICAL	2 IDENTICAL (ADJ/OPP)	0 IDENTICAL
CLUSTERS	37%	27%	33% (20% / 13%)	3%
ANOMALIES	19%	15%	54% (18% / 36%)	13%
EXTREMUM	29%	21%	23% (17% / 5%)	28%

Table 2. Orientation consistency across participants per task.

Herein, we analyze the data on a per-task basis, specifically reporting on a breakdown per physicalization and per participant. We then discuss the relation to our hypothesis, providing a first characterization of the effects of perspective on the perception of physicalizations. Throughout this section we use descriptive statistics to report our findings.

CLUSTERS

Orientation consistency of clusters per physicalization

In this section we elaborate on the *orientation consistency* of identified clusters across orientations per physicalization (Table 3). To reiterate, a cluster is a set of objects a participant considered to 'belong together' based on their relation to one another, i.e. 4 clusters refers to 4 sets of objects that the participant perceived as grouped.

PHYS	4 IDENTICAL	3 IDENTICAL	2 IDENTICAL (ADJ/OPP)	0 IDENTICAL
#1	10	4	6 (3 / 3)	0
#2	6	5	9 (4 / 5)	0
#3	2	3	13 (9 / 4)	2
#4	8	3	8 (6 / 2)	1
#5	5	12	3 (1 / 2)	0
#6	13	5	1 (1 / 0)	1

Table 3. Orientation consistency of clusters per physicalization.

For phys1 10 and phys6 13 participants saw identical clusters across all 4 orientations (OC-4), for phys5 12 participants saw identical clusters across 3 orientations (OC-3) and for phys2 9 and phys3 13 participants saw identical clusters across 2 orientations (OC-2). Lastly, for phys4 8 participants saw identical clusters across 2 orientations (OC-2) and 8 saw identical clusters across all 4 (OC-4). To summarize, orientation strongly influences the identification of clusters.

Orientation consistency of clusters per participant

Considering *orientation consistency* for identifying clusters per participant, 6 participants frequently saw 4 identical clusters across all orientations (OC-4), with the outlier P5 who was 100% consistent across physicalizations. Further, 5 participants frequently saw identical clusters across 3 orientations (OC-3) and 6 participants saw identical clusters across 2 (OC-2). Lastly, 3 participants did not have a predominant OC value. Among all participants there were 3 who perceived 4 distinct clusters across all orientations. In summary, 11 participants have an *orientation consistency* of more than 50%, meaning that they perceived the same clusters across 3-4 orientations when looking at the same physicalization.

PHYS	# CLUSTERS	1C	# 2C	# 3C	# 4C	# 5C	# ANOMALIES	# EXTREMUM
#1	3	1			2		7	10
#2	10	1	2	1	6		10	16
#3	17		2	5	7	3	14	36
#4	11		1	3	5	2	16	31
#5	12	1	2	4	3	2	9	42
#6	6		4	1	1		11	31

Table 4. Details the number of unique clusters, anomalies and extremum identified by participants per physicalization.

Cluster characteristics per physicalization

The second column of Table 4 provides an overview of all occurrences of clusters that were identified per physicalization. In the consecutive columns a subdivision per number of clusters is provided, for example for phys1 a total of 3 occurrences of clusters were identified of which 1 type of 1 cluster (1C) and 2 types of 4 clusters (4C-T1 and 4C-T2) (Figure 4).

However, as illustrated by Table 4 the number of clusters does not provide complete insight, for example for phys3 participants identified up to *7 different types of 4 clusters*. The total number of clusters in combination with the diversity in types of clusters is indicative for *orientation consistency*. For example, a higher total number of occurrences and/or cluster types implies a greater *inconsistency*. In the following section we compare the frequently observed clusters, per orientation, for each physicalization and provide details on their characteristics.

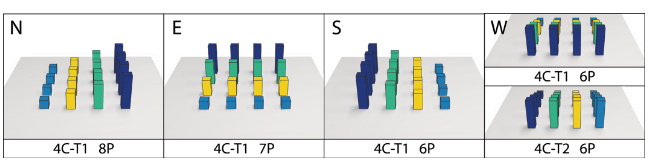

Figure 8. Phys1: Different types of clusters per orientation. #P is the number of participants that clustered phys1 in this way.

Physicalization 1 – 3 occurrences of clusters were identified, of which 1C (1 cluster) occurred frequently across all 4 orientations, in 8 to 11 participants (Figure 3). The second most observed occurrence was for 3 orientations, North, East and South, 4C-T1 (4 clusters, type 1) and for 1 orientation, West, 4C-T1 and 4C-T2 were each observed as frequently (Figure 8). This could be explained by the continuity observed either horizontally or longitudinally from the participant. In contrast, in West, the occlusion caused by the tall cuboids closest to the participant, is probably the reason for it being perceived either as columns or rows.

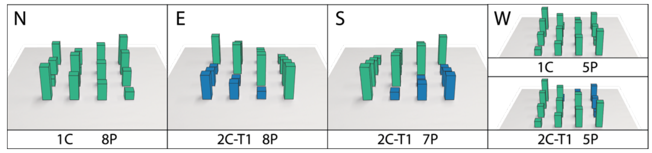

Figure 9. Phys2: Different types of clusters per orientation.

Physicalization 2 – 10 occurrences of clusters were identified, of which 1C and 2C-T1 occurred frequently across the orientations (Figure 9). For the North orientation the participants frequently saw 1 cluster. This could be explained by the occlusion of the smaller cubes furthest from the participant, making it appear as 1 cluster. In orientation East and South, 2C-T1 was frequently seen, which could be explained by the less elevated part of the physicalization being closest to the participant. Therefore, not occluding the other cubes and/or creating a distinct boundary between the two clusters.

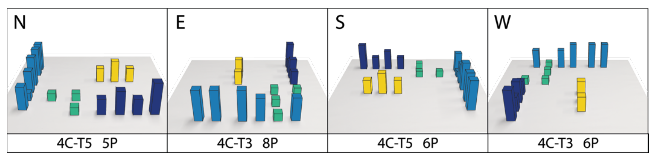

Figure 10. Phys3: Different types of clusters per orientation.

Physicalization 3 – 17 occurrences of clusters were identified, of which 2 types of 4 clusters occurred most frequently across the orientations. More specifically, for the opposites North and South, 4C-T5 was observed frequently, whereas for East and West this was 4C-T3 (Figure 10). The difference between the 4C-T3 and 4C-T5 lies in the clustering of the cubes. For North and South, one cube is occluded, and it becomes part of the longitudinal cluster on the side. The three other cubes are clustered together. In East and West, none of the four cubes are occluded, forming a continuous path.

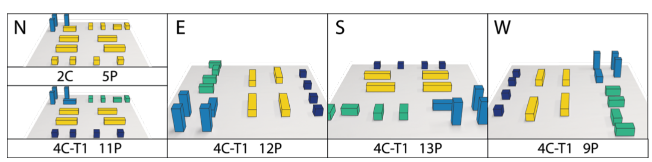

Figure 11. Phys4: Different types of clusters per orientation.

Physicalization 4 – 11 occurrences of clusters were identified of which 4C-T1 occurred frequently across all 4 orientations, in 9 to 13 participants (Figure 11). Additionally, 5 participants observed 2C in the North orientation.

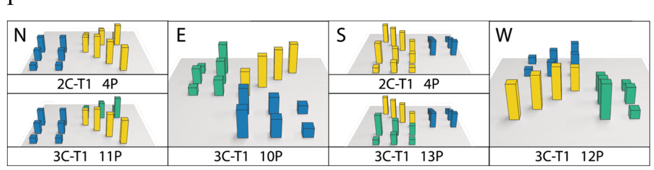

Figure 12. Phys5: Different types of clusters per orientation.

Physicalization 5 – 12 occurrences of clusters were identified, of which 3C-T1 occurred frequently across all 4 orientations, in 10 to 13 participants (Figure 12). Further, 2C-T1 was observed by 4 participants in both North and South.

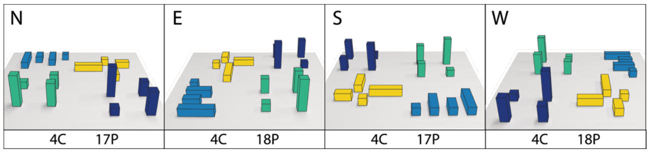

Figure 13. Phys6: Different types of clusters per orientation.

Physicalization 6 – 6 occurrences of clusters were identified, of which 4C-T1 occurred frequently across all 4 orientations, in 17 to 18 participants (Figure 13). This could be explained by the clear distinction between internal and external proximity of the clusters and therefore a general lack of occlusion.

Discussion: The effects of orientation on data clustering

A common theme that influences participants' ability to form clusters is the role of occlusion in perceiving the properties of the physicalization: proximity, continuity, and atomic orientation. We can categorize these into:

Continuity occlusion: A perceived array of objects seemingly intersected, preventing the participant from seeing the full continuity of them.

Proximity occlusion: The perceived distance between objects, appearing either further or closer together, depending on the perspective, preventing the participants from seeing the true proximity.

Atomic orientation occlusion: The perceived similarity between objects of different forms or perceived discrepancies between objects of similar forms, due to atomic orientation differences. For example, if you observe a cuboid directly in line with its square face it may appear as a cube.

For phys1-3 (Figure 8, 9, 10) *continuity occlusion* lead to different clusters being identified by participants across orientations. For example, in phys1 we can see for West orientation there was a split between 2 cluster types. This could be due to the constant continuity of the physicalization being occluded by the taller cuboids, resulting in some participants observing 4C-T2. Similarly, in phys2 for East and South orientations, part of the constant continuity of the physicalization is occluded, creating a clear boundary between parts of the physicalization – which is not present in the other orientations. Finally, in phys3 the North and South most common cluster types were different than in East to West. As with in the other physicalizations, the constant continuity of the smallest cubes in North and South is occluded resulting in them not being considered as part of the same cluster.

For phys4 and phys5 (Figure 11, 12) both *continuity occlusion* and *proximity occlusion* influenced the formation of clusters across orientations. For example, in phys5, for North and South orientations 2C-T1 was perceived by multiple participants. Compared to East and West, in the North orientation the front-right cluster occludes the back right-cluster affecting the perception of cluster proximity and continuity making the right cluster appear as one. This is the same in the South orientation, however the continuity appears to be not occluded. For phys4, 5 participants clustered the physicalization by 2C as opposed to the more common 4C-T1. We believe this is due to a combination of *continuity*, *proximity occlusion* but also *atomic orientation occlusion.* For example, from the North orientation in phys4 the upright cuboids have their atomic orientation partially occluded due to the distance from the participant, resulting in perceived similarities in form, creating one potential cluster. In contrast, in the South orientation, these are clearly not occluded as they are closer to the participant and thus visible.

However, for phys6 (Figure 13), all participants identified the same types of clusters across the 4 orientations. We infer that this is because of the stark external proximity between 4 potential clusters. Moreover, there is a large amount of ambiguity across the clusters in terms of continuity and atomic orientation, leading to most participants using proximity as the main parameter for clustering.

In summary, *proximity occlusion*, *continuity occlusion*, and *atomic orientation occlusion* influence the way in which participants formed clusters. Most notably, the strategies some participants adopted to form clusters, i.e. initial anomaly filtering, meant that occluded aspects of a physicalization influenced the formation of clusters directly.

FILTERING

Orientation consistency of anomalies per physicalization

Table 5 shows the differences in *orientation consistency* of indicated anomalies across orientations per physicalization. To reiterate, an anomaly is a cluster of objects that initially caught the participants' attention. In summary, for all 6 physicalizations the majority of the participants indicated identical anomalies across 2 orientations (OC-2). In this case, OC-2 were mostly adjacent to each other rather than opposite.

PHYS	4 IDENTICAL	3 IDENTICAL	2 IDENTICAL (ADJ/OPP)	0 IDENTICAL
#1	7	3	9 (6 / 3)	1
#2	7	1	10 (5 / 5)	2
#3	3	6	8 (6 / 2)	3
#4	2	4	8 (8 / 0)	6
#5	4	2	14 (9 / 5)	0
#6	0	5	12 (9 / 3)	3

Table 5. Orientation consistency for anomalies per phys.

Orientation consistency of anomalies per participant

If we look at *orientation consistency* for indicating anomalies per participant, 3 participants frequently saw 4 identical anomalies across all orientations (OC-4), 1 participant saw 3 identical anomalies (OC-3) and 11 participants saw 2 identical anomalies (OC-2). Lastly, 4 participants did not have a predominant OC value for filtering anomalies.

Anomaly characteristics per physicalization

The eighth column of Table 4 shows an overview of all occurrences of anomalies that were indicated per physicalization. Below we will compare the frequently observed anomalies per orientation for each physicalization and provide details on their characteristics.

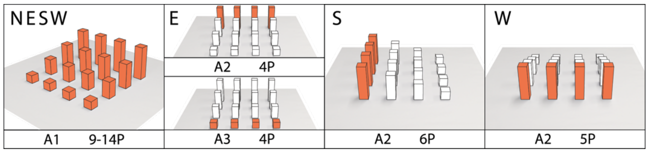

Figure 14. Phys1: Different types of anomalies per orientation. A# refers to the type of anomaly identified by participants.

Physicalization 1 – 7 occurrences of anomalies were indicated, of which A1 occurred frequently across all orientations, in 9 to 14 participants (Figure 14). A1 is when the participants indicated that the physicalization was anomalous as a whole or no anomaly at all. This can be explained by symmetrical proximity and clear continuity despite potential occlusion. The second most observed anomalies were A2 and A3 across the orientations East, South and West.

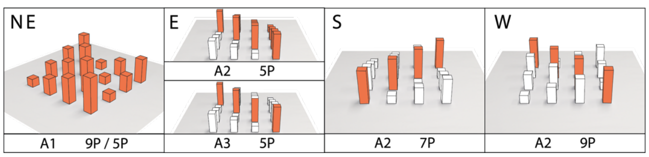

Figure 15. Phys2: Different types of anomalies per orientation.

Physicalization 2 – 10 occurrences of anomalies were indicated, of which 3 anomaly types occurred most often, across orientations (Figure 15). A1 is when the participants indicated that the visualization was either anomalous as a whole or no particular anomaly at all, which occurred only frequently in the North orientation, in 9 participants. For East the 3 anomaly types occurred equally (5 participants each) and for South and West A2 occurred most often.

Physicalization 3 – 14 occurrences of anomalies were indicated, of which A1 (Figure 16) occurred frequently across all 4 orientations, in 9 to 13 participants. The anomaly across orientations of phys3 can be explained due to the large external proximity between the 3 objects in the center and the surrounding objects in the physicalization, separating them from each other regardless of orientation.

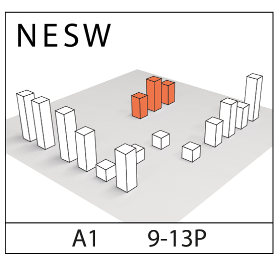

Figure 16. Phys3 anomaly.

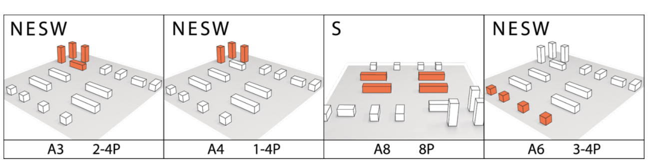

Figure 17. Phys4: Different anomalies across orientations.

Physicalization 4 – 16 occurrences of anomalies were indicated, of which A3, A4, A6 and A8 occurred frequently across orientations (Figure 17). However, no clear majority of participants were consistent across these 4 types.

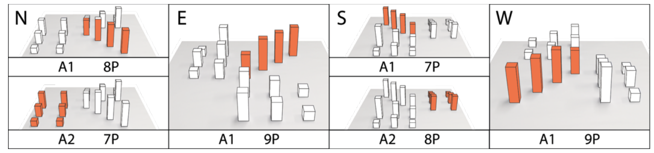

Figure 18. Phys5: Different anomalies for 2 orientation pairs.

Physicalization 5 – 9 occurrences of anomalies were indicated, of which A1 and A2 occurred frequently across orientations. As illustrated in Figure 18 in the opposite orientations East and West A1 occurred the most, whereas in North and South A1 and A2 occurred almost as frequent.

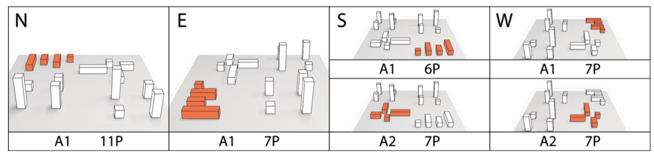

Figure 19. Phys6: Different anomalies for 2 orientation pairs.

Physicalization 6 – 11 occurrences of anomalies were indicated. For North and East A1 was observed frequently, whereas for South and West this was A1 or A2 (Figure 19).

Discussion: The effects of orientation on data anomalies

Reflecting on the results described above, we observed two different themes that influenced participants' filtering of anomalies. Firstly, participants described that they were more likely to observe non-occluded objects initially and therefore more likely to perceive them as anomalous.

Non-occluded clusters could either be the tallest objects and/or with a proximity noticeably distant from other clusters. For example, for phys1, the second most frequent observed cluster was the 4 tallest cuboids, which are not occluded from a single angle. Phys3 is an example of the 3 central objects being clearly distinct from the surrounding objects due to the large external proximity between them. In relation to this, non-linear positioning, such as tall, diagonally placed objects, was more likely to be perceived as anomalous by participants, for example in phys2 and phys5.

There is a clear relation between the previous clustering results and filtering anomalies, specifically the initial anomalies observed, and the most frequent clusters formed in each of the physicalizations. For instance, in phys2 the North orientation was generally identified as wholly anomalous or containing no anomalies. This was similar to the clustering for this orientation – mostly clustered as a whole.

Again, looking at phys2, in the 3 other orientations the diagonal, tallest, minimally occluded set of objects were identified as anomalous. This relates to participants' method of clustering the physicalizations into 2 clusters based on the level of occlusion, specifically from these orientations.

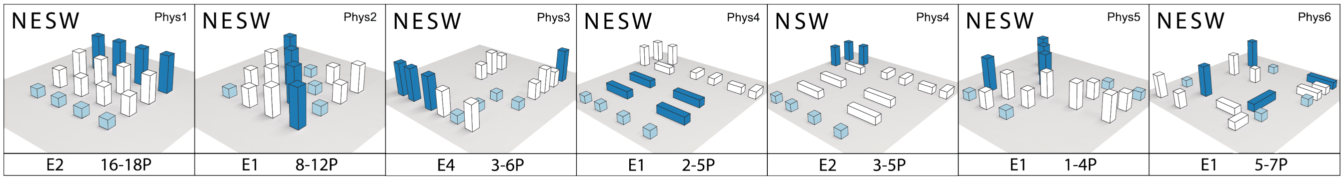

Figure 20. The most frequent indicated extremum per physicalization. E# refers to the type of extremum identified by participants.

FINDING EXTREMUM

Orientation consistency of extremum per physicalization

In this section we elaborate on the *orientation consistency* of indicated extremes across orientations per physicalization (Table 6). To reiterate, an extremum is what a participant perceived as one or more lowest and highest values. In summary, for phys1 14 and phys2 8 participants saw identical extremum across all orientations (OC-4), for phys4 7 participants saw identical extremum across 2 orientations (OC-2) and for both phys3 and phys5 10 participants saw distinct extremum across all orientations (OC-1). For phys6 6 participants saw identical extremum across 3 orientations (OC-3) and 6 saw distinct extremum across all 4 (OC-1).

PHYS	4 IDENTICAL	3 IDENTICAL	2 IDENTICAL (ADJ/OPP)	0 IDENTICAL
#1	14	5	0	1
#2	8	5	5 (5 / 0)	2
#3	4	2	4 (4 / 0)	10
#4	4	4	7 (3 / 4)	5
#5	2	3	5 (3 / 2)	10
#6	3	6	5 (5 / 0)	6

Table 6. Orientation consistency for extremum per phys.

Orientation consistency of extremum per participant

If we look at *orientation consistency* for indicating extremum per participant, 7 participants mostly saw 4 identical extremum across all orientations (OC-4), 1 participant saw 3 identical extremum (OC-3), 2 participants saw 2 identical extremum (OC-2) and 6 participants saw 4 distinct extremum across orientations (OC-1). Lastly, 4 participants did not have a predominant OC value for finding extremum.

Extremum characteristics per physicalization

In the ninth column of Table 4 you can find an overview of all occurrences of extremum that were indicated per physicalization. As the variety in occurrences of extremum was high, we report on the frequently observed extremum for each physicalization, instead of per orientation, and provide an overall description on their characteristics (Figure 20).

Physicalization 1 – 10 occurrences of extremum were indicated, of which E2 was observed most frequently across orientations, in 16 to 18 participants.

Physicalization 2 – 16 occurrences of extremum were indicated, of which E1 was observed most frequently across orientations, in 8 to 12 participants.

Physicalization 3 – 36 occurrences of extremum were indicated, of which E4 was observed most frequently across orientations, in 3 to 6 participants.

Physicalization 4 – 31 occurrences of extremum were indicated, of which E1 and E2 were observed most frequently across orientations, in 2 to 5 participants. The observation of E2 can be explained by the difference in *atomic orientation* of the upright cuboids in the back left.

Physicalization 5 – 42 occurrences of extremum were indicated, of which E1 was observed frequently across orientations, in 1 to 4 participants.

Physicalization 6 – 31 occurrences of extremum were indicated, of which E1 was observed frequently across orientations, in 5 to 7 participants.

To summarize, agreement on physicalization extremum was generally low, with the exception of phys1 and phys2. The frequently observed extremums were generally defined by the absolute size of the objects - i.e. the smallest and largest.

Discussion: The effects of orientation on data extremum

From 2D information visualization literature, finding the extremum involves: *"Finding data cases possessing an extreme value of an attribute over its range within a data set"* [2]. In the case of physicalizations, we can attribute this to objects that are the smallest and largest in the set in terms of absolute size. Our results support this, as participants frequently found extremum across physicalizations to be the smallest and largest objects. However, participants were influenced by other factors as well, such as the location of the object(s) on the grid and/or their atomic orientation.

As can be derived from Table 4 (column 9), there were many variations in the number of occurrences for different extremums per physicalization. Looking holistically at the different extremum found by the participants the following behaviors were observed: (i) Participants chose singular objects as the extremum for the entire physicalization, either as maximum or minimum values. (ii) Participants assigned a cluster of objects as the collective extremum for the entire physicalization, either as a maximum or minimum value. (iii) Participants assigned a single extremum on a per-cluster basis, for which they identified either maximum or minimum values.

The inconsistencies in these behaviors can be attributed to a common sense-making process the participants adopted that has emerged over the course of the discussion of our results. The occlusion of objects during the initial anomaly filtering process lead to varied cluster formations and subsequently influenced the strategy for extremum identification, not only within a single physicalization but also within a participant.

For physicalizations with limited external proximity variances, such as phys1 and phys2, agreement on extremum was much higher. This could be due to the low proximity variance or symmetrical nature of the physicalization, but it could also be due to limited occlusion of initially filtered anomalies. In this case, the tallest objects in phys1 and phys2.

DISCUSSION

Our study shows the direct influence of user orientation on the perception of exemplars of physicalizations and physical information in general. Participants did not interpret information consistently which is indicative for physical layouts not being reliable in conveying data. Across participants, a common theme of a "sense-making" process arose. Parallels can be drawn between the information retrieval tasks of 2D visualizations and the tasks undertaken in the study, i.e. *clustering*, *filtering*, and *finding the extremum*. While the study was designed to draw parallels from 2D information visualization, it was not clear how changing perspective would influence information retrieval and overall sense-making. From the results discussed, we characterize the differences across perspectives in a sense-making process.

We postulate that occlusion is one of the primary reasons for inconsistencies in sense-making and information retrieval across perspectives. Occlusion can be differentiated by the properties of a physicalization, in terms of *proximity* occlusion, *continuity* occlusion, and *atomic orientation* occlusion. Occlusion directly affected the participants in their *filtering* of the data to identify anomalies. Participants adopted and described a strategy of initially *filtering* the data before *clustering*, and then finding the *extremums* based on the clusters.

While the influence of perspective, and thus occlusion, on information retrieval seems trivial, we provide a first characterization of the effect of changing perspectives on the sense-making process for *proximity*, *continuity* and *atomic orientation* occlusions. We will further discuss how to build upon this initial understanding to create recommendations and physicalization frameworks for designers.

This paper was successful in providing an initial characterization of the effect of changing perspective, however the study has certain limitations. All exact occurrences of identified clusters, anomalies and extremum were recorded. In the current study, due to the intentional ambiguity of the tasks, especially in finding the extremum, some occurrences showed partially overlapping elements. For example, similar objects were indicated as extremum across participants and orientations, however they were not 100% identical to each other. There could be patterns and similar behaviors extracted from the data based on this overlap. Subsequently, this meant that there was a more detailed depiction of participant's sense-making process that we have yet to understand. Further, participants conveyed their strategies and decision-making processes through body language, hand gestures and verbal clarifications. Future work could explore this characterization further through qualitative analysis and interpreting the patterns in extremum, clusters and anomalies.

The scope of this study was to examine the influence of user orientation on a physical structure independent of context. Therefore, we explicitly chose not to include indicators of data mapping, meaning participants could not use context to inform their decisions on filtering, clustering and finding extremum. While we hypothesized that linear absolute size would be a clear gauge for scale and extremes, we observed that participants also used other factors such as location on the grid and/or atomic orientation. Future work is necessary to further explore the implications of context on people's sense-making of physical information and examine the relation between data mapping scales of discrete objects and pre-attentive visual properties of a whole physicalization.

Regarding our measurement method of perspective, there were two limitations. (i) The angular view and height of participants may have influenced the perception of physical properties. However, we were interested in physicalizations that could be holistically explored, not just viewed from a fixed angle. (ii) We only examined 4 orientation conditions of 90 degrees, while physicalizations in general can be explored from 360 degrees. Our reason for constraining participant and physicalization movement is that we wanted to explicitly examine user orientation in a systematic way by reproducing the viewing biases. Further, we observed that participants exhibited minimal head and torso movements in order to readily perform the tasks, which indeed supports the notion of occlusion influencing sense-making. Future work is necessary to investigate the influence of angular view, the use of body motion on sense-making and the holistic exploration around the circumference of a physicalization.

Other routes for future work include (i) investigating the influence of perspective during reconfiguration tasks: how could physical properties facilitate, persuade or hinder the user? Also, do parallels exist between the strategies described in this paper and strategies in reconfiguration? (ii) This work focused on 3D bar chart-like physicalizations, but other shapes and forms could be examined using similar methodologies. (iii) Finally, understanding whether collaboration around physicalizations amplifies or reduces the effects measured in our studies.

CONCLUSION

In this paper we examined the relation between user orientation and information perception of physicalizations. We conducted an experiment with 6 exemplar physicalizations and presented them from 4 different perspectives to evaluate information retrieval. Our study shows the direct relation between orientation and user perception of physical information. We also provide a first characterization of *orientation consistency* and observed the sense-making process guided by different types of occlusion. To conclude, it is imperative to carefully consider how the design of physicalizations might yield ambiguous perceptions of the information being conveyed. Future work is necessary to build upon this initial understanding to create generalizable frameworks and guidelines for physicalizations that consider the way in which information is manifested.

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