

Technische Universität Berlin

Faculty IV / Computational Psychology

# Measuring perceived similarity using Inverse Multidimensional Scaling in three dimensions

Bachelor Thesis

|                  |                             |
|------------------|-----------------------------|
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# Eigenständigkeitserklärung

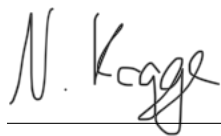
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Berlin, den 22.06.2026

A handwritten signature in black ink, appearing to read 'N. Kogge', is written above a horizontal line.

Unterschrift

# Danksagung

An dieser Stelle möchte ich mich bei allen bedanken, die mich bei der Erstellung dieser Bachelorarbeit unterstützt haben. Mein besonderer Dank gilt Dr. Guillermo Aguilar, für die fachliche Begleitung im Rahmen des Prüfungsprozesses. Ebenso danke ich allen Teilnehmerinnen und Teilnehmern der Studie für ihre Zeit, ihre Sorgfalt und ihren Beitrag zur Datenerhebung. Ihre Unterstützung hat die Durchführung dieser Arbeit wesentlich ermöglicht.

# Abstract

Spatial arrangement tasks allow participants to express perceived similarity by placing objects closer together or farther apart. While such tasks are an efficient way to capture many similarity relations at once, the design of the interaction space may influence how these relations are expressed. In particular, it remains unclear whether allowing placements in three dimensions leads to more consistent or more variable similarity judgments than a conventional two-dimensional arrangement. This study examines this question using a single-trial iMDS task in which each participant arranged the same stimulus set once in a 2D condition and once in a 3D condition. The resulting arrangements were compared descriptively across participants and between conditions to assess how consistently participants organized the stimuli and how strongly each individual arrangement matched a reference pattern computed from the remaining participants in the same condition. The present data show that 2D arrangements were more similar across participants, whereas 3D arrangements showed more variable spatial organizations. Compared with the participant-excluded reference pattern, both conditions showed clear but imperfect overlap in the expressed similarity structure, with lower overlap in the 3D condition. These findings suggest that interaction dimensionality influences how perceived similarities are externalized in spatial arrangement tasks and that adding a third placement dimension may increase individual variability in the resulting representations.



# Zusammenfassung

Räumliche Anordnungsaufgaben ermöglichen es Teilnehmenden, wahrgenommene Ähnlichkeit auszudrücken, indem sie Objekte näher beieinander oder weiter voneinander entfernt platzieren. Während solche Aufgaben eine effiziente Möglichkeit darstellen, viele Ähnlichkeitsbeziehungen auf einmal zu erfassen, kann die Gestaltung des Interaktionsraums beeinflussen, wie diese Beziehungen ausgedrückt werden. Insbesondere bleibt unklar, ob Platzierungen in drei Dimensionen zu konsistenteren oder variableren Ähnlichkeitsurteilen führen als eine konventionelle zweidimensionale Anordnung. Diese Studie untersucht diese Frage mithilfe einer Single-Trial-iMDS-Aufgabe, in der jede teilnehmende Person dasselbe Stimulusset einmal in einer 2D-Bedingung und einmal in einer 3D-Bedingung anordnete. Die resultierenden Anordnungen wurden deskriptiv über Teilnehmende hinweg und zwischen Bedingungen verglichen, um zu beurteilen, wie konsistent Teilnehmende die Stimuli organisierten und wie stark jede individuelle Anordnung mit einem Referenzmuster übereinstimmte, das aus den verbleibenden Teilnehmenden derselben Bedingung berechnet wurde. Die vorliegenden Daten zeigen, dass 2D-Anordnungen zwischen Teilnehmenden ähnlicher waren, während 3D-Anordnungen variablere räumliche Organisationen zeigten. Verglichen mit dem unter Ausschluss der jeweiligen teilnehmenden Person berechneten Referenzmuster zeigten beide Bedingungen eine deutliche, aber unvollkommene Überlappung in der ausgedrückten Ähnlichkeitsstruktur, mit geringerer Überlappung in der 3D-Bedingung. Diese Befunde legen nahe, dass die Interaktionsdimensionalität beeinflusst, wie wahrgenommene Ähnlichkeiten in räumlichen Anordnungsaufgaben externalisiert werden, und dass das Hinzufügen einer dritten Platzierungsdimension die individuelle Variabilität in den resultierenden Repräsentationen erhöhen kann.

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# 1. Introduction

Human object perception is remarkably complex. Objects vary along multiple perceptual attributes, such as color, shape, and size, which are encoded simultaneously by the visual system. Understanding how these attributes are internally represented and organized into perceptual structure is a central question in visual perception research (Goldstone, 1994b; Kriegeskorte et al., 2008).

These representations support similarity judgments, which are important for categorization and grouping (Goldstone, 1994b). To study such structures, researchers use quantitative methods such as *Multidimensional Scaling* (MDS), which reconstruct spatial configurations from perceived similarities between stimuli. Distances in these embeddings reflect underlying perceptual relations and can reveal latent dimensions such as brightness or shape (Goldstone, 1994b; Kruskal, 1964).

Classical MDS often asks participants to provide many separate pairwise judgments and assumes stable dissimilarity relations across items. A simpler alternative is *inverse multidimensional scaling* (iMDS), where participants arrange stimuli directly in space and dissimilarities are derived from the resulting distances rather than from explicit comparisons. This makes the task more intuitive and efficient (Goldstone, 1994a; Hout et al., 2013; Kriegeskorte and Mur, 2012).

The present implementation uses a single-trial iMDS task in which all stimuli are arranged simultaneously. Most iMDS studies rely on two-dimensional (2D) arrangements, which may compress multi-attribute information into fewer degrees of freedom and limit the expressiveness of spatial representations. The absence of a recorded depth coordinate may constrain how complex similarity relations are expressed (Verheyen et al., 2016; Kriegeskorte and Mur, 2012).

This work investigates whether adding a third recorded interaction coordinate is associated with differences in how participants express similarity. More specifically, it describes how increased interaction dimensionality relates to the organization, variability, and between-participant consistency of the resulting arrangements.

## 1.1. Previous work

Classical multidimensional scaling (MDS) typically relies on pairwise similarity ratings or pairwise comparisons. To reduce task duration and participant fatigue while preserving a geometric interpretation of similarity, *spatial arrangement* paradigms ask participants to position many stimuli at once so that Euclidean distances approximate perceived dissimilarity (Kruskal, 1964; Goldstone, 1994a; Hout et al., 2013).

Beyond perceptual stimuli, arrangement tasks have also been applied to conceptual domains such as word meaning. Richie et al. (2020) showed that distances derived from the Spatial Arrangement Method (SpAM) can capture high-dimensional semantic structure and correlate strongly with other semantic similarity estimates, supporting SpAM as a reliable method even when the latent structure is not naturally low-dimensional. SpAM operationalizes similarity by asking participants to drag stimuli on a 2D plane

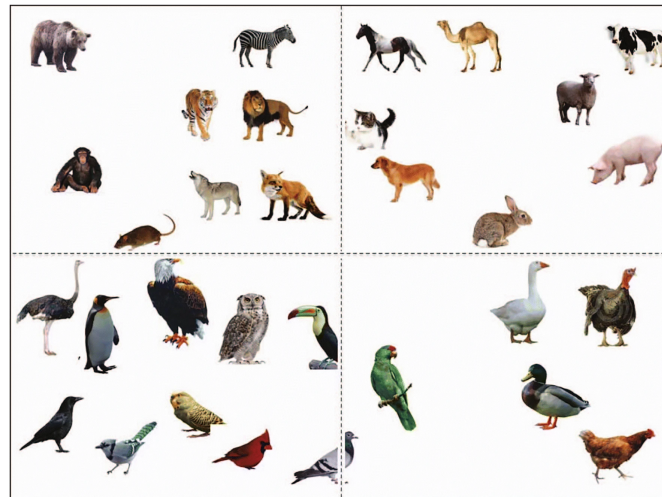


Figure 1.: Example of a 2D SpAM arrangement reflecting several semantic distinctions. The main x/y layout distinguishes mammals (top) from birds (bottom) and wild (left) from domestic (right). Within each quadrant, the animals are additionally organized by size and by whether they are commonly eaten by humans. Source: Hout and Goldinger (2016, Fig. 1, DOI: 10.1037/xge0000144).

(fig. 1) so that similar items are placed close together. Distances in the final layout can then be converted into a dissimilarity matrix and analyzed with MDS-style techniques. Hout et al. (2013) argued that SpAM is a fast and efficient alternative to pairwise procedures and showed that it can recover meaningful similarity structure across multiple stimulus sets. A key extension of this approach is the combination of evidence across

*multiple* arrangements in order to approximate a full dissimilarity matrix for larger stimulus sets (fig. 2).

In systems neuroscience, Kriegeskorte and Mur (2012) described a related inverse approach in which pairwise dissimilarities are inferred from multiple 2D arrangements (fig. 2), thereby linking arrangement behavior to representational similarity analysis (RSA), a framework for comparing the relational structure of representations across behavioral, computational, or neural data.

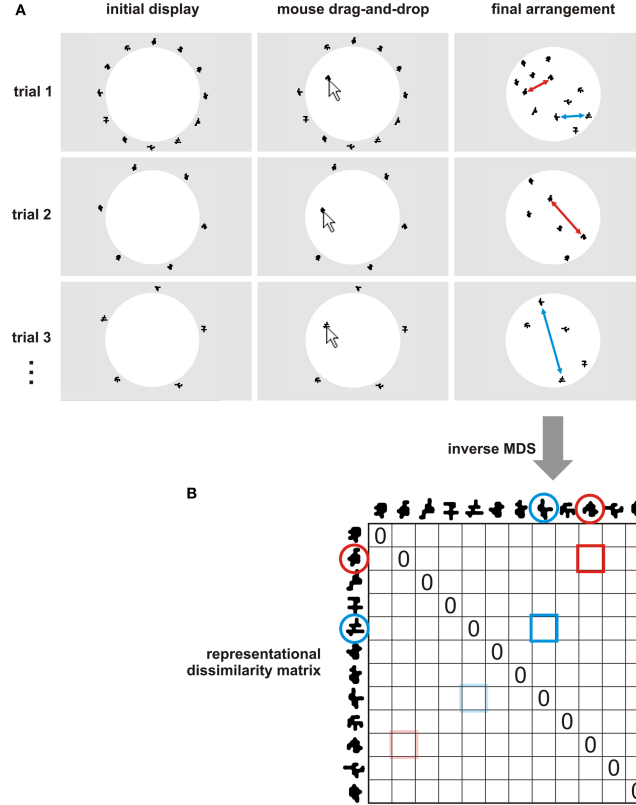


Figure 2.: Illustration of the multi-arrangement method. Participants arrange items represented as on-screen icons by drag and drop, placing similar objects close together and dissimilar objects farther apart. Multiple 2D arrangements are then statistically combined and transformed into a representational dissimilarity matrix (RDM). Adapted after the multi-arrangement illustration in (Kriegeskorte and Mur, 2012).

Rather than collecting all pairwise judgments directly, this approach infers an underlying dissimilarity matrix from multiple arrangements. It substantially reduces the number of explicit responses required while preserving detailed information about representational structure (Kriegeskorte and Mur, 2012). However, this efficiency comes at a potential



cost: because these arrangements are typically restricted to two-dimensional interaction spaces, the expressiveness of complex similarity relations may be constrained. This raises the question of how the dimensionality of the interaction space itself influences the resulting representations.

## 1.2. Research question

Prior work has established spatial arrangement paradigms as an efficient alternative to exhaustive pairwise similarity judgments: participants communicate perceived similarity by arranging items so that inter-item distances approximate psychological dissimilarity (Hout et al., 2013). This logic has been shown to remain informative beyond purely perceptual stimuli; for example, Richie et al. (2020) demonstrated that SpAM-derived distances can recover meaningful, effectively high-dimensional semantic structure. Building on the same intuition, iMDS combines evidence across *multiple* 2D arrangements, often based on subsets of stimuli, to infer a full representational dissimilarity matrix (RDM) while reducing participant workload (Kriegeskorte and Mur, 2012). At the same time, restricting interaction to a 2D surface may constrain how complex similarity relations can be expressed and may introduce geometric compression or layout artifacts (Verheyen et al., 2016). These considerations motivate the present work and lead to the following research question: **How does adding a third dimension affect the outcomes of iMDS spatial arrangement experiments?**

## 2. Method

For this study, a custom experimental interface was developed for a single-trial iMDS spatial arrangement task, drawing on established spatial arrangement and iMDS paradigms. Whereas prior work typically restricts interaction to two-dimensional arrangements, the present implementation was extended to support both 2D and 3D placement within the same general task logic. The aim was not to reproduce a full multi-arrangement iMDS procedure, but to compare how the available interaction space changes the way participants externalize perceived similarity in one complete arrangement.

To make this comparison interpretable, the stimulus set, task instruction, and basic response format were kept constant across conditions. Participants always arranged the same objects according to perceived similarity, so that similar stimuli should be placed close together and dissimilar stimuli farther apart. What varied between conditions was the number of recorded interface coordinates and the interaction mechanics required to use them:  $x$  and  $y$  in the 2D condition, and  $x$ ,  $y$ , and  $z$  in the 3D condition (Goldstone, 1994a; Hout et al., 2013; Kriegeskorte and Mur, 2012).

### 2.1. Study Design

The study used a within-subject design in which each participant completed both task conditions. This design was chosen because the central comparison concerns how the same participant structures the same stimulus set when the placement space changes. Holding the participant sample and stimuli constant reduces variability that would otherwise arise from between-group differences and makes the descriptive 2D–3D comparison more direct.

The stimulus format is comparable to the abstract icon-based stimuli used by Kriegeskorte and Mur (2012), while the interface was developed specifically for this thesis. The methodological emphasis is a controlled comparison of two interaction spaces built around the same stimulus set and task instruction. The resulting arrangements are described relative to established 2D multi-arrangement and iMDS procedures in terms of arrangement-derived similarity patterns and related agreement and variability metrics.

### 2.1.1. Stimuli

This study used a body-silhouette stimulus set chosen to match the abstract, icon-based stimulus format used in multi-arrangement and iMDS work by Kriegeskorte and Mur (2012). These stimuli consist of simplified, high-contrast body poses that are easy to discriminate visually while remaining relatively abstract compared with photographs of everyday objects. Using the same controlled silhouettes in both conditions reduces the risk that differences between the 2D and 3D arrangements are driven by changes in stimulus content rather than by the available spatial degrees of freedom.

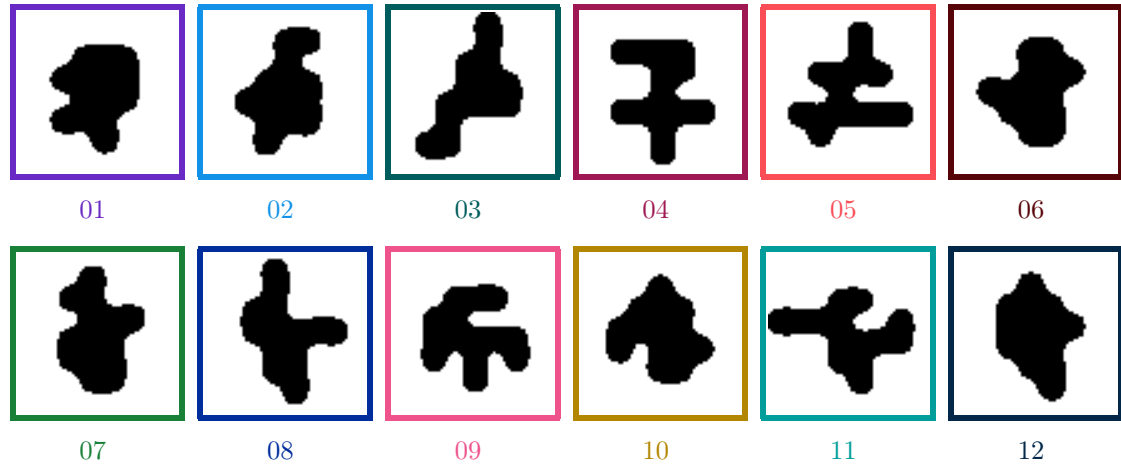


Figure 3.: Body-silhouette stimulus set used in the present task, following the abstract stimulus format used in (Kriegeskorte and Mur, 2012).

The silhouette format also supports the intended similarity judgment: relative to photographs of everyday objects, it reduces obvious semantic cues and encourages participants to rely more strongly on posture, limb configuration, and global shape (Goldstone, 1994b). In addition, all stimuli share a common presentation format, reducing the risk that background, texture, or lighting dominate the arrangement instead of the intended structural differences in pose and shape.

### 2.1.2. Apparatus

The experiment was conducted on a MacBook Pro using an external mouse. An adjustable headrest was provided to improve comfort and to reduce possible posture-related variation across participants. The main task was performed on an external laboratory monitor that was temporarily raised to an appropriate viewing height. Because the interface

was introduced through an instructional video, both the laptop screen and the external monitor were used during the session.

### **2.1.3. Variables**

The independent variable was interaction dimensionality (2D vs. 3D), defined as the number of recorded interface coordinates available for stimulus placement. The dependent variables captured between-participant consistency, consensus agreement, variability, and geometric discrepancy of the resulting spatial configurations.

### **2.1.4. Participants**

Seven participants (aged 24–55) were recruited and received compensation. All had normal or corrected-to-normal vision and were familiar with basic digital interfaces. The experiment was conducted in the university vision lab under controlled lighting conditions: ceiling lights were switched off and the setup was enclosed by black curtains to minimize external light.

### **2.1.5. Task and Procedure**

The experiment used a within-subject design with two conditions (2D and 3D). In each condition, participants completed a single arrangement trial in which they organized the stimulus set (fig. 3) on the basis of perceived similarity, such that similar objects were positioned closer together and dissimilar objects farther apart. This single-trial iMDS task draws on the central idea of inverse multidimensional scaling, namely that similarity judgments are expressed through relative distances in a configuration space.

Participants were allowed to manipulate all stimuli freely throughout the task. This included moving, repositioning, and iteratively refining placements until they were satisfied with the resulting configuration. No explicit constraints were imposed on placement strategy, allowing both global structuring processes (e.g., cluster formation or axis construction) and local adjustments (e.g., fine-tuning distances between individual items).

Before the experiment, participants watched an instructional video explaining the task, the interface, and the available interaction mechanics. This was followed by a short

tutorial phase designed to familiarize them with the system. After completing the tutorial, participants proceeded to the main experiment, which began with either the 2D or the 3D condition according to a manually assigned starting order. Because the sample size was odd, the starting condition could only be approximately balanced across participants rather than perfectly counterbalanced. All participants completed both conditions, yielding a total of  $7 \times 2 = 14$  spatial configurations. No time limit was imposed, allowing participants to complete the task at their own pace and encouraging careful, deliberate similarity judgments.

#### 2.1.6. Debriefing

Each session concluded with a semi-structured debriefing interview intended to capture participants' subjective experiences and to contextualize the observed spatial arrangements. The interview focused on (i) **task strategies**, (ii) **differences in behavior between the 2D and 3D conditions**, and (iii) **the perceived usefulness of the additional coordinate**. Additional questions addressed axis interpretation, interface usability, and whether properties of the interface influenced participants' judgments. Participants were also asked about perceived task difficulty, possible order effects, and what they would change if they were to repeat the task. Finally, they indicated whether their arrangements were guided more strongly by global structure or by local relationships.

## 2.2. Experimental Interface

### 2.2.1. Software

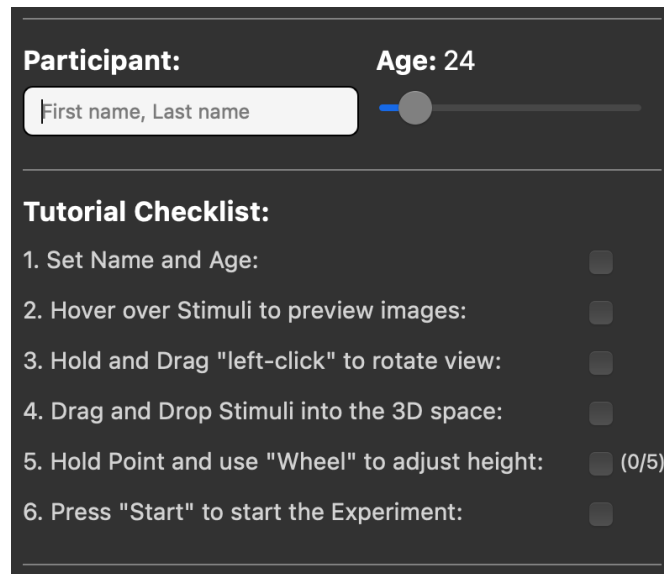
The experimental interface was implemented in Python to support rapid prototyping and reproducible data collection. The graphical user interface (GUI) was built with **PySide6** (Qt for Python), providing a stable, cross-platform desktop application framework with fine-grained control over user interaction. Responsive visualization and stimulus manipulation were implemented with **PyQtGraph**, which is designed for high-performance graphics on top of Qt and integrates closely with **NumPy** for efficient array-based computation. Smooth 3D rendering and real-time feedback were supported through an **OpenGL** backend via Python OpenGL bindings (e.g., PyOpenGL).

### 2.2.2. Initialization

Before the main experiment began, participants saw a start screen on which the experimental condition (2D or 3D) could in principle be selected. In the present study, however, the condition itself was assigned by the experimenter in order to control for order effects. After the experimenter clicked the *Start experiment* button, the main interface opened and participants took control of the session. The interface then guided them through several phases while maintaining a consistent interaction flow.

Participants first entered their name and age. They then completed a tutorial checklist designed to familiarize them with the interface and its interaction mechanics. The tutorial (fig. 4) ensured that all participants reached a comparable level of familiarity before beginning the main task, and completion of the checklist was required to unlock the *Start* button.

The specific tutorial criteria and progress indicators differed slightly between the 2D and 3D versions to reflect their different interaction demands. These tasks had no effect on the experimental outcome and served only as a controlled environment for exploration and practice.



The image shows a dark-themed user interface for participant registration and a tutorial checklist. At the top, it displays 'Participant:' followed by a text input field containing 'First name, Last name' and 'Age: 24' next to a horizontal slider. Below this is a section titled 'Tutorial Checklist:' containing six items, each with a checkbox. The first five items are unchecked, while the sixth is checked. The fifth item has a '(0/5)' next to its checkbox.

| Item                                            | Progress                            |
|-------------------------------------------------|-------------------------------------|
| 1. Set Name and Age:                            | <input type="checkbox"/>            |
| 2. Hover over Stimuli to preview images:        | <input type="checkbox"/>            |
| 3. Hold and Drag "left-click" to rotate view:   | <input type="checkbox"/>            |
| 4. Drag and Drop Stimuli into the 3D space:     | <input type="checkbox"/>            |
| 5. Hold Point and use "Wheel" to adjust height: | <input type="checkbox"/> (0/5)      |
| 6. Press "Start" to start the Experiment:       | <input checked="" type="checkbox"/> |

Figure 4.: Participant registration and tutorial components for the 2D and 3D conditions. Once participants had entered their name and age and started the experiment, they could not change this information during the session. Completed items were marked with a checkmark. For brevity, only the 3D tutorial is shown, as the 2D version differed only in minor respects, such as the absence of scene rotation.

### 2.2.3. Interface Components

Below these introductory elements, the interface consisted of four organized modules that provided (i) clear control over trial state, (ii) consistent interaction with the stimulus set, and (iii) transparent feedback about system events relevant to data integrity.

#### Stimulus List

The Stimuli panel fig. 5a represents the stimulus set as a numbered, scrollable list that provides a stable reference for navigation and selection. Each stimulus is represented by a draggable token with a random initial assignment, which reduces the risk that fixed ordering cues influence placement decisions. This design also supports an unambiguous mapping between interface elements, stimulus identifiers, and logged data records, which is important for reconstructing trials and ensuring consistent downstream analysis.

#### Preview Window

The preview component fig. 5b displays the currently selected stimulus at a larger scale when participants hover over the corresponding item in the stimulus list or arrangement area. This is particularly useful for visually minimal stimuli such as silhouettes (fig. 3), for which small differences in shape or pose may be difficult to discriminate in the main arrangement area because of size, occlusion, or visual crowding. By providing a clearer reference view, the preview reduces the likelihood that placements are driven by visibility artifacts rather than intended similarity judgments.

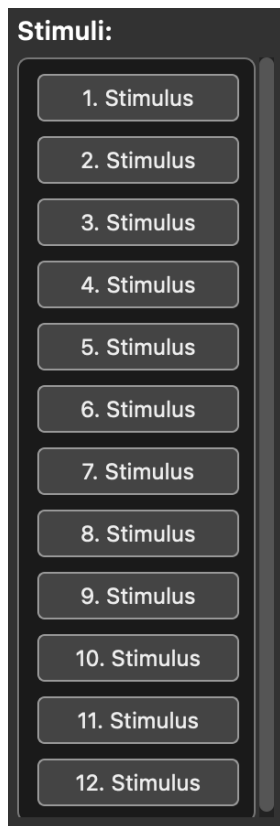
#### Control Panel

Below the preview window, adjacent control buttons provided trial-level functions (fig. 5c). *Start* initialized a trial and enabled arrangement interaction in a well-defined state. As noted above, any interaction before the trial started served only as tutorial practice and had no effect on the recorded outcome. *Reset* restored the current configuration to a predefined baseline by returning stimuli to their initial positions in the stimulus list, allowing participants to recover from accidental placements without terminating the trial. *Set View* standardized the camera perspective, which was particularly important in 3D interaction, and *Submit* finalized the trial and stored the final arrangement. In practice,

these components were tied to a simple state machine (e.g., *Submit* became available only after *Start* and after all stimuli had been placed), reducing accidental submissions and helping to ensure that logged configurations corresponded to completed judgments.

## Event Terminal

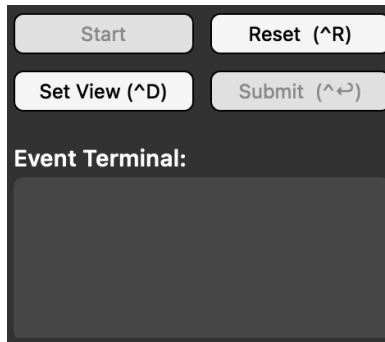
Finally, the event terminal fig. 5c, which was originally developed for debugging, displays a chronological record of relevant system events and user actions (e.g., trial start, reset, submission, and view changes). Although it is not essential for task completion, this additional transparency may improve perceived system responsiveness and user confidence.



(a) Stimuli Container



(b) Stimulus Preview



(c) Buttons & Event Terminal

Figure 5.: Interface components. The figure arrangement reflects the layout of the initial interface.



#### 2.2.4. Interaction in the 2D Condition

The 2D arrangement area (fig. 6) is one of the central interaction spaces in which participants externalize similarity judgments by arranging stimuli on a planar surface. Each stimulus, represented by a movable token (figs. 3 and 5a), could be selected and repositioned using mouse-based left-click-and-drag. Participants were free to iteratively adjust placements throughout the trial, allowing both local refinements and broader structural organization. The task was intentionally continuous rather than discrete: participants could make incremental changes until the configuration reflected their current best estimate of the similarity structure.

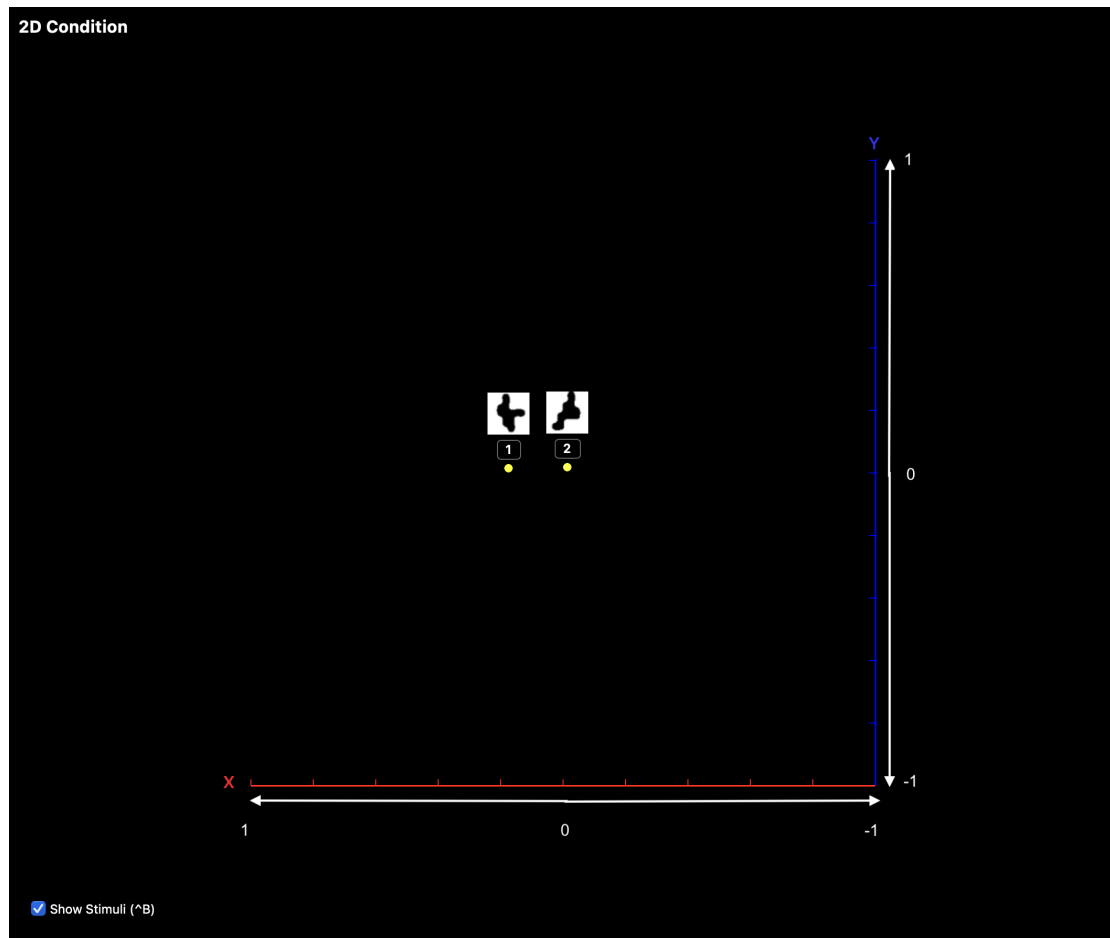


Figure 6.: Arrangement area in the 2D condition. The white axis arrows were added for illustration and were not visible to participants. Internally, all axes used a coordinate range of  $[-1, 1]$ . In the lower-left corner, *Show Stimuli* could be toggled to hide or show the miniature stimulus previews above the points.

### 2.2.5. Interaction in the 3D Condition

The 3D condition fig. 7 implements the core task in a volumetric workspace by adding a third recorded interface coordinate to the placement space. Stimuli can be distributed across three coordinates, providing additional degrees of freedom for separating clusters, ordering items, or resolving conflicts that may arise when multiple similarity relations cannot be represented simultaneously in a plane. The scene can be rotated with left-click-and-drag, which is important for accurate placement because it supports judgments about relative position along all coordinates. The mouse scroll wheel adjusts a stimulus along this  $y$  coordinate without changing its horizontal location in the current view, and it can be combined with horizontal movement to exploit the full 3D workspace.

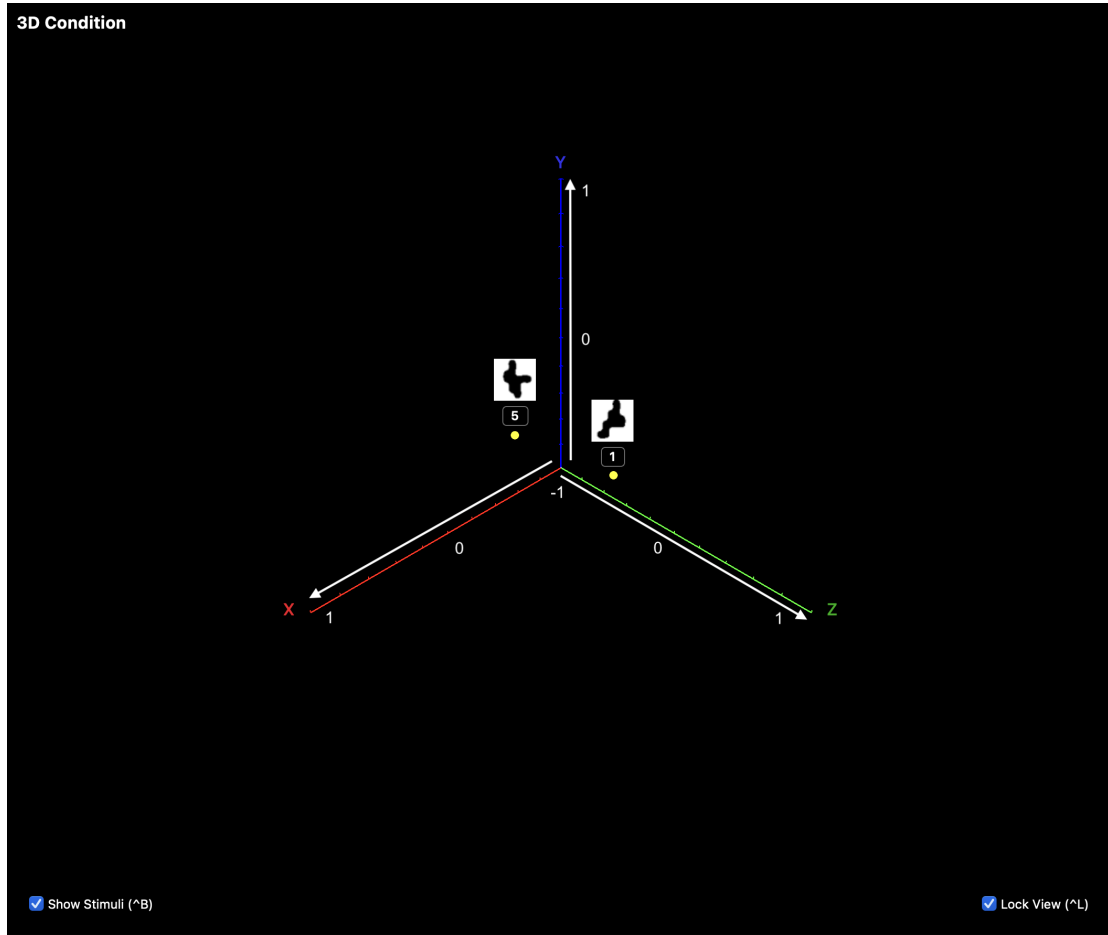


Figure 7.: Arrangement area in the 3D condition. All features described in fig. 6 also apply here. In addition, participants could use *Lock View* in the lower-right corner to enable or disable left-click scene rotation. This was useful when they wanted to reposition stimuli without changing the scene viewport.

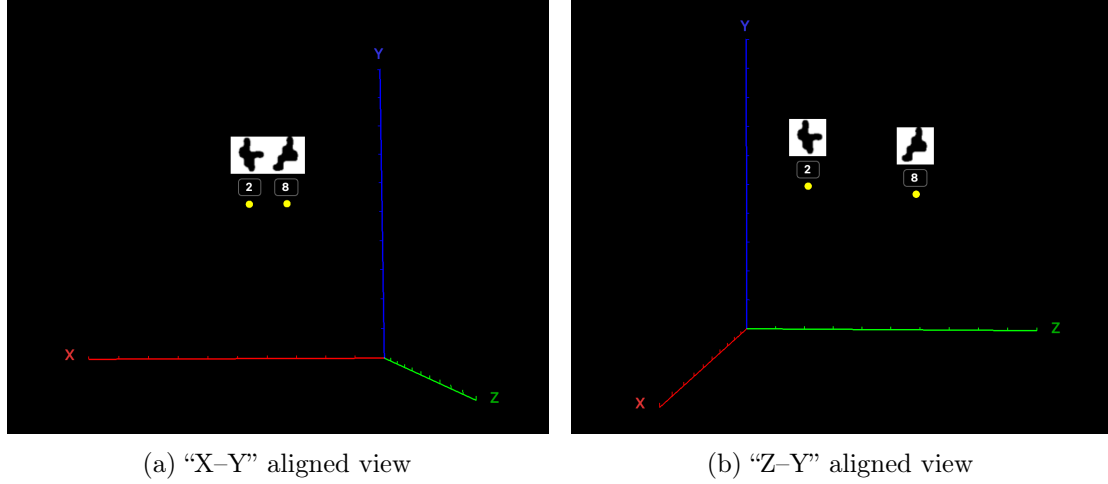


Figure 8.: These panels illustrate why scene rotation is important in the 3D condition: objects that appear close together from one viewpoint may in fact be separated along the additional recorded coordinate.

Ultimately, the 3D condition is not simply a larger workspace but a qualitatively different interaction medium. The additional recorded axis enables spatial strategies that are difficult to realize in 2D, as illustrated in figs. 6 and 8. Participants can separate otherwise crowded groups without forcing large displacements in the plane and can place intermediate cases at different  $z$  positions while preserving local neighborhoods. In principle, this design reduces the need for compromises that arise when several similarity relations compete for the same planar layout.

## 2.3. Data Analysis

### 2.3.1. Preprocessing and configuration matrix

The experimental data consist of the raw interface coordinates recorded for each participant under both conditions (2D and 3D). Each trial yields a configuration of stimulus coordinates in a common interface reference frame. The exported  $x$ ,  $y$ , and  $z$  columns are fixed recorded interface coordinates rather than view-relative screen coordinates. In the 2D condition, the  $z$  coordinate is constrained to zero, whereas in the 3D condition all three recorded coordinates are available. Each data file contains metadata (participant identifier, completion time, and condition), followed by a list of stimuli and their corresponding coordinates. These logged coordinate configurations form the basis of all

subsequent analyses. In particular, pairwise distances between stimuli are derived directly from these recorded positions to construct dissimilarity representations (cf. Eq. (2.4)). Coordinate tables shown later in the Results and Appendix are rounded for readability, but the reported quantitative analyses refer to the recorded interface coordinates before table formatting.

| Variable    | Description                                             |
|-------------|---------------------------------------------------------|
| Participant | Unique identifier for each participant                  |
| Condition   | Experimental condition (2D or 3D)                       |
| stimuli_png | Filename of the stimulus image                          |
| x           | Horizontal interface coordinate                         |
| y           | Vertical interface coordinate                           |
| z           | Third recorded interface coordinate (0 in 2D condition) |

Table 1.: Structure of the recorded spatial arrangement data for each trial.

Each trial produces a final configuration in which  $n$  stimuli are placed in a low-dimensional interface space. In the 2D condition, placements are restricted to the  $xy$ -plane ( $z = 0$ ), whereas in the 3D condition all three spatial axes are available. Formally, each stimulus  $i$  is represented by a coordinate vector. For the 2D condition,

$$\mathbf{x}_i^{2D} = (x_i, y_i) \in \mathbb{R}^2 \quad (2.1)$$

and for the 3D condition,

$$\mathbf{x}_i^{3D} = (x_i, y_i, z_i) \in \mathbb{R}^3. \quad (2.2)$$

Collecting all stimuli yields the participant- and condition-specific configuration matrix

$$\mathbf{X}^{(p,d)} = \begin{bmatrix} (\mathbf{x}_1^{(p,d)})^\top \\ \vdots \\ (\mathbf{x}_n^{(p,d)})^\top \end{bmatrix} \in \mathbb{R}^{n \times d}, \quad d \in \{2, 3\}. \quad (2.3)$$

Here,  $n$  denotes the number of stimuli,  $d$  denotes the dimensionality of the recorded arrangement space ( $d = 2$  for the 2D condition and  $d = 3$  for the 3D condition), and  $p$  indexes the participant. Unless stated otherwise, this notation applies to all following formulas; when two participants are compared, the participant indices are written as  $a$  and  $b$ . This matrix representation provides a compact description of each spatial

arrangement and serves as the basis for deriving pairwise dissimilarities (cf. Eq. (2.4)) and all subsequent analyses.

### 2.3.2. Relational Dissimilarity

Given a final configuration  $\mathbf{X}^{(p,d)} \in \mathbb{R}^{n \times d}$ , a pairwise dissimilarity matrix  $\mathbf{D}^{(p,d)} \in \mathbb{R}^{n \times n}$  is obtained by computing Euclidean distances between all stimulus coordinates:

$$D_{ij} = \|\mathbf{x}_i - \mathbf{x}_j\|_2 = \sqrt{\sum_{k=1}^d (x_{ik} - x_{jk})^2}, \quad d \in \{2, 3\}. \quad (2.4)$$

The matrix  $\mathbf{D}$  is symmetric with  $D_{ii} = 0$  and provides a complete relational description of the spatial configuration. The recorded coordinates are exported on a common  $[-1, 1]$  interface scale, but the analyses use the Euclidean pairwise distances in  $\mathbf{D}$  directly unless explicitly noted otherwise. Spearman correlations, leave-one-out consensus distances, Shepard analyses, and k-nearest-neighbor (kNN) neighborhoods are all based on these Euclidean distances (see next subsections). For visualization, some distance matrices and Shepard plots are displayed on a normalized  $[0, 1]$  scale for readability and comparability; this presentation scaling does not alter rank-based comparisons such as Spearman correlations or kNN neighborhoods.

The dissimilarity matrix  $\mathbf{D}$  can therefore be interpreted as a relational representation of the spatial configuration, with each entry encoding the arrangement-derived dissimilarity between two stimuli.

In representational similarity analysis (RSA)-style analyses, dissimilarity vectors are typically constructed by excluding the diagonal and retaining only one triangular portion of the matrix (Nili et al., 2014). This avoids redundant information and prevents illusory effects such as artificially inflated correlations or biased similarity estimates caused by duplicated entries and trivial zero self-distances.

### 2.3.3. Spearman Correlation and Procrustes-Aligned RMSE

To assess the agreement of arrangement-derived dissimilarity structures, two complementary measures are used (Nili et al., 2014; Gower, 1975). Let  $\mathbf{X}^{(a,d)}$  denote the participant-specific configuration matrix, that is, the same configuration matrix introduced in Eq. (2.3), here indexed by participant  $a$  and condition  $d$ . Let  $\mathbf{D}^{(a,d)}$  denote

the corresponding dissimilarity matrix derived from Eq. (2.4). Given the exploratory character of the study, the small sample, and the dependence among pairwise comparisons, the following measures are reported descriptively rather than as inferential tests. First, between-participant consistency is quantified as the pairwise Spearman rank correlation between participant-specific dissimilarity matrices within the same condition:

$$\rho_{ab}^{(d)} = \rho_s(\text{vec}_{\Delta}(\mathbf{D}^{(a,d)}), \text{vec}_{\Delta}(\mathbf{D}^{(b,d)})), \quad d \in \{2, 3\}. \quad (2.5)$$

Here,  $\text{vec}_{\Delta}(\cdot)$  denotes the vectorization of the upper triangular part of the matrix excluding the diagonal (cf. Eq. (2.4)). In addition, within-participant cross-dimensional correspondence is assessed by comparing each participant's 2D and 3D representations:

$$\rho_a^{(2,3)} = \rho_s(\text{vec}_{\Delta}(\mathbf{D}^{(a,2)}), \text{vec}_{\Delta}(\mathbf{D}^{(a,3)})). \quad (2.6)$$

This measure provides a descriptive summary of how similar the relational rank orderings are across interaction dimensionalities within the same participant (cf. Eq. (2.4)). Second, Procrustes alignment provides a descriptive measure of geometric similarity between participant configurations after optimal transformation. To reduce differences in position, orientation, and scale within each dimensionality, configurations are first centered and normalized:

$$\tilde{\mathbf{X}}_a^{(d)} = \frac{\mathbf{X}^{(a,d)} - \bar{\mathbf{X}}_a^{(d)}}{\|\mathbf{X}^{(a,d)} - \bar{\mathbf{X}}_a^{(d)}\|_F}, \quad d \in \{2, 3\}. \quad (2.7)$$

where  $\bar{\mathbf{X}}_a^{(d)}$  denotes the matrix whose rows all equal the centroid of participant  $a$ 's configuration in condition  $d$ , and  $\|\cdot\|_F$  denotes the Frobenius norm.

Geometric discrepancy is then quantified using a normalized Procrustes-aligned root mean squared error (RMSE):

$$\text{RMSE}_{ab}^{(d)} = \frac{1}{\sqrt{nd}} \left\| \tilde{\mathbf{X}}_a^{(d)} - T_d(\tilde{\mathbf{X}}_b^{(d)}) \right\|_F, \quad d \in \{2, 3\}. \quad (2.8)$$

where  $T_d$  denotes the Procrustes transformation in condition  $d$  after centering and scale standardization, allowing rotation and, if necessary, reflection and scaling. This procedure is implemented with `scipy.spatial.procrustes`, and pairwise RMSE is

reported on the aligned standardized coordinates. Lower values indicate lower residual geometric discrepancy within this normalized Procrustes summary (cf. Eq. (2.3)). This normalization reduces confounding by differences in position, orientation, and scale (Gower, 1975). Because the 2D and 3D summaries are computed in coordinate spaces with different dimensionality, condition-level RMSE values are interpreted descriptively under this normalization rather than as a direct relational-agreement measure.

#### 2.3.4. Shepard Analysis

The Shepard diagram assesses how well arrangement-derived distances agree with a reference relational structure (Shepard, 1962). For each participant  $a$  and condition  $d \in \{2, 3\}$ , participant-specific distances  $D_{ij}^{(a,d)}$  are derived directly from the submitted configuration (cf. Eq. (2.4)).

In the absence of an external ground truth, the reference dissimilarity for participant  $a$  in condition  $d$  is defined as the average distance between stimuli  $i$  and  $j$  across all *other* participants in the same condition. This leave-one-out consensus reference serves as the comparison reference in the Shepard and k-nearest-neighbor analyses below:

$$\delta_{ij}^{(d,-a)} = \frac{1}{N_d - 1} \sum_{\substack{k=1 \\ k \neq a}}^{N_d} D_{ij}^{(k,d)}. \quad (2.9)$$

In words,  $\delta_{ij}^{(d,-a)}$  is the mean pairwise distance for stimulus pair  $(i, j)$  computed from all participants except the one currently being evaluated. This formulation ensures that the evaluated participant does not contribute to the reference used to assess that participant, thereby avoiding circularity. Here,  $N_d$  denotes the number of participants in condition  $d$ . The Shepard diagram therefore plots participant-specific distances  $D_{ij}^{(a,d)}$  against the corresponding consensus distances  $\delta_{ij}^{(d,-a)}$  obtained from the remaining participants only. To obtain a single summary measure for each task condition ( $d \in \{2, 3\}$ ), all participant-by-stimulus-pair observations are pooled into one dataset, rather than fitting separate models per participant and averaging their coefficients. Specifically, the vectors  $D_{ij}^{(a,d)}$  (participant-specific distances) and  $\delta_{ij}^{(d,-a)}$  (leave-one-out consensus distances) for all participants  $a = 1, \dots, N_d$  and all stimulus pairs  $i < j$  are concatenated, and a single ordinary least squares (OLS) regression is fitted to this combined set. This pooled

regression estimates how strongly participant-specific distances align with the between-participant consensus across the entire condition. The resulting predicted distances are given by:

$$\hat{D}_{ij}^{(a,d)} = \hat{\beta}_{0,d} + \hat{\beta}_{1,d} \delta_{ij}^{(d,-a)}, \quad d \in \{2, 3\}, \quad (2.10)$$

and the resulting pooled coefficient of determination is denoted

$$R_{d,\text{pooled}}^2 = 1 - \frac{\sum_{a=1}^{N_d} \sum_{i < j} \left( D_{ij}^{(a,d)} - \hat{D}_{ij}^{(a,d)} \right)^2}{\sum_{a=1}^{N_d} \sum_{i < j} \left( D_{ij}^{(a,d)} - \bar{D}^{(d)} \right)^2}, \quad d \in \{2, 3\}. \quad (2.11)$$

where  $\bar{D}^{(d)}$  is the grand mean of all arrangement-derived distances across participants and stimulus pairs, and  $\hat{D}_{ij}^{(a,d)}$  is the predicted value from the pooled regression (cf. Eq. (2.10)). Higher values indicate stronger agreement between participant-specific distances and the leave-one-out consensus reference. All condition-wise Shepard values reported in the Results correspond to  $R_{d,\text{pooled}}^2$ .

### 2.3.5. k-Nearest Neighbor Preservation

To assess local structure, this thesis uses a simple k-nearest-neighbor (kNN) overlap measure based on neighborhood-preservation criteria for dimensionality reduction (Lee and Verleysen, 2009; Venna and Kaski, 2006). Based on the dissimilarity matrices  $\mathbf{D}^{(a,d)}$  (cf. Eq. (2.4)) and the leave-one-out consensus structure  $\delta^{(d,-a)}$  (cf. Eq. (2.9)), the set of the  $k$  nearest neighbors of a stimulus  $i$  is defined as the indices corresponding to the  $k$  smallest pairwise distances.

For each participant  $a$ , stimulus  $i$ , and condition  $d \in \{2, 3\}$ , the overlap between neighborhoods in the reference space  $N_k^{\delta^{(d,-a)}}(i)$  and the participant-specific distance space  $N_k^{\mathbf{D}^{(a,d)}}(i)$  is computed as:

$$\text{kNN}_{k,(a,d)}(i) = \frac{\left| N_k^{\delta^{(d,-a)}}(i) \cap N_k^{\mathbf{D}^{(a,d)}}(i) \right|}{k}. \quad (2.12)$$

The metric takes values in  $[0, 1]$ , where higher values indicate stronger overlap between local neighborhoods relative to the leave-one-out consensus reference. For each neighborhood size  $k$ , the condition-level preservation curve is defined as the arithmetic mean



across all participants and stimuli:

$$\overline{\text{kNN}}_d(k) = \frac{1}{N_d n} \sum_{a=1}^{N_d} \sum_{i=1}^n \text{kNN}_{k,(a,d)}(i), \quad d \in \{2, 3\}. \quad (2.13)$$

Here,  $n$  denotes the number of stimuli. Due to the limited number of stimuli ( $n = 12$ ), kNN preservation is inherently constrained for large  $k$ . As  $k$  approaches  $n - 1$ , the overlap between neighborhoods is mathematically forced to increase. Therefore, interpretation focuses primarily on small and intermediate neighborhood sizes, where the measure is most sensitive to meaningful structural differences.

### 2.3.6. Axis Variance

To descriptively summarize how variance is distributed across the recorded interface coordinates, axis variance was computed separately for each participant  $a$  and condition  $d$  using the raw logged coordinates in their original interface frame (i.e., without rotational realignment or other coordinate standardization):

$$\sigma_{k,(a,d)}^2 = \text{Var}\left(\mathbf{X}_k^{(a,d)}\right), \quad k \in A_d, \quad A_2 = \{x, y\}, \quad A_3 = \{x, y, z\}. \quad (2.14)$$

To compare axis use across participants within a condition, these variances were converted into participant-specific variance ratios:

$$r_{k,(a,d)} = \frac{\sigma_{k,(a,d)}^2}{\sum_{j \in A_d} \sigma_{j,(a,d)}^2}. \quad (2.15)$$

Condition-level axis summaries are then obtained by averaging these participant-specific ratios:

$$\bar{r}_{k,d} = \frac{1}{N_d} \sum_{a=1}^{N_d} r_{k,(a,d)}. \quad (2.16)$$

Higher variance along an interface axis indicates greater spread on that recorded coordinate; in 3D, non-zero variance along  $z$  indicates use of the additional recorded coordinate. Because these summaries remain tied to the raw interface frame, they are interpreted descriptively, and the Results report the mean variance ratios  $\bar{r}_{k,d}$ .

### 3. Results

This section presents the results as descriptive patterns rather than inferential tests. It first describes qualitative observations to provide an intuitive overview of the spatial arrangements across conditions. It then reports three complementary summaries: between-participant consistency of arrangement-derived RDMs, agreement with a leave-one-out consensus reference, and use of the recorded interface axes.

#### 3.1. Illustrative Outcomes

##### 3.1.1. Spatial Arrangement Patterns

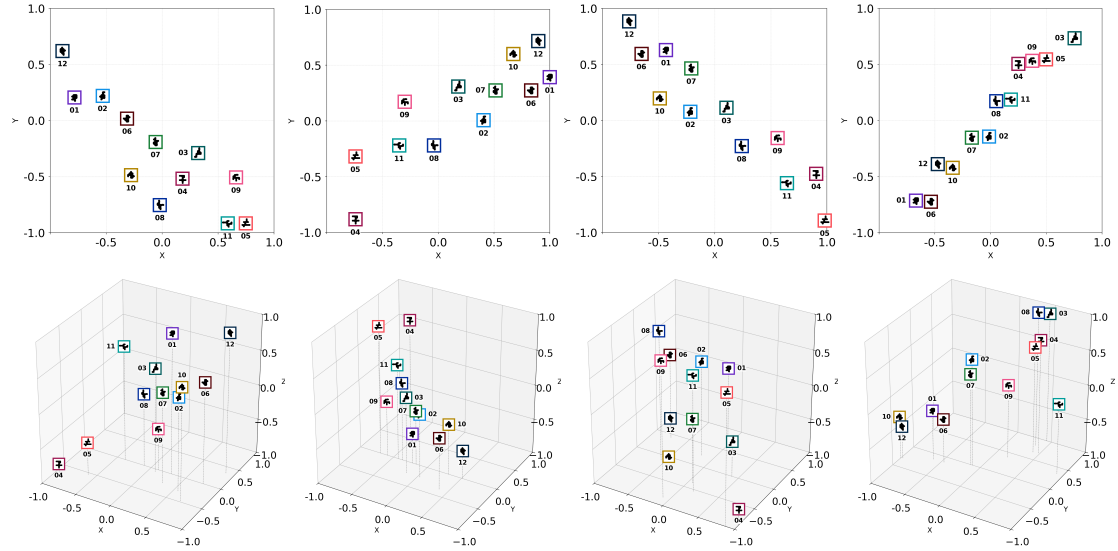


Figure 9.: Selected illustrative spatial arrangements for participants 3–6 in the 2D (top row) and 3D (bottom row) conditions. Each column corresponds to one participant (left to right). Points represent individual stimuli positioned according to participant-specific similarity judgments.

Figure 9 shows four selected illustrative spatial arrangements from the 2D and 3D conditions. These examples are not used as inferential evidence, but they illustrate the kind of organizational patterns that the subsequent RDM-based summaries quantify.

Across these examples, the 2D configurations often show a more elongated or approximately linear structure, with stimuli arranged along a dominant trend in the plane. This

visual pattern is consistent with a more constrained placement space in which several similarity relations must be expressed through two recorded coordinates.

Apart from the previously shown spatial arrangements from participants 3–6, participants 1, 2, and 7 showed more idiosyncratic patterns across the two conditions. Participant 1 arranged the stimuli in the 2D condition in an approximately linear pattern. Participant 2 organized the stimuli into column-like structures along the y-axis in 2D. Participant 7 relied primarily on the y-axis, while expanding the configuration along the x-axis in the 2D condition.

Across all participants, stimuli in the 3D condition are distributed across all three recorded coordinates. These configurations vary more strongly in how they occupy the  $z$  coordinate and the surrounding volumetric workspace, indicating a broader range of submitted spatial organizations rather than a single shared 3D layout strategy. Remaining participant-specific overviews are provided in Appendix C.

### 3.1.2. From Spatial Arrangements to Dissimilarity Matrices

Using the configuration representation defined in Eqs. 2.1–2.3, each submitted arrangement is represented as stimulus coordinates in a  $d$ -dimensional interface space. These coordinate tables document the submitted placements, but they are not interpreted stimulus by stimulus in the main analysis. Instead, they provide the raw basis for the relational measures. A full participant-level example is provided in Appendix C; Table 7 shows the coordinate tables, arrangements, and RDMs for one participant.

The spatial configurations are transformed into relational dissimilarity matrices (RDMs) by applying the Euclidean distance measure (cf. Eq. 2.4) to all pairs of coordinate vectors. This converts absolute positions into arrangement-derived dissimilarities: nearby stimuli yield small pairwise distances, whereas distant stimuli yield larger ones. Thus, each arrangement is summarized as a relational pattern over all stimulus pairs.

Pairwise distances are invariant to translation, rotation, and reflection. Because 2D and 3D differ in coordinate dimensionality, absolute distance magnitudes are interpreted cautiously. The main comparisons therefore focus on rank-based structure, agreement with condition-specific consensus references, and descriptive coordinate-use summaries.

### 3.1.3. Illustrative Cross-Dimensional RDM Patterns

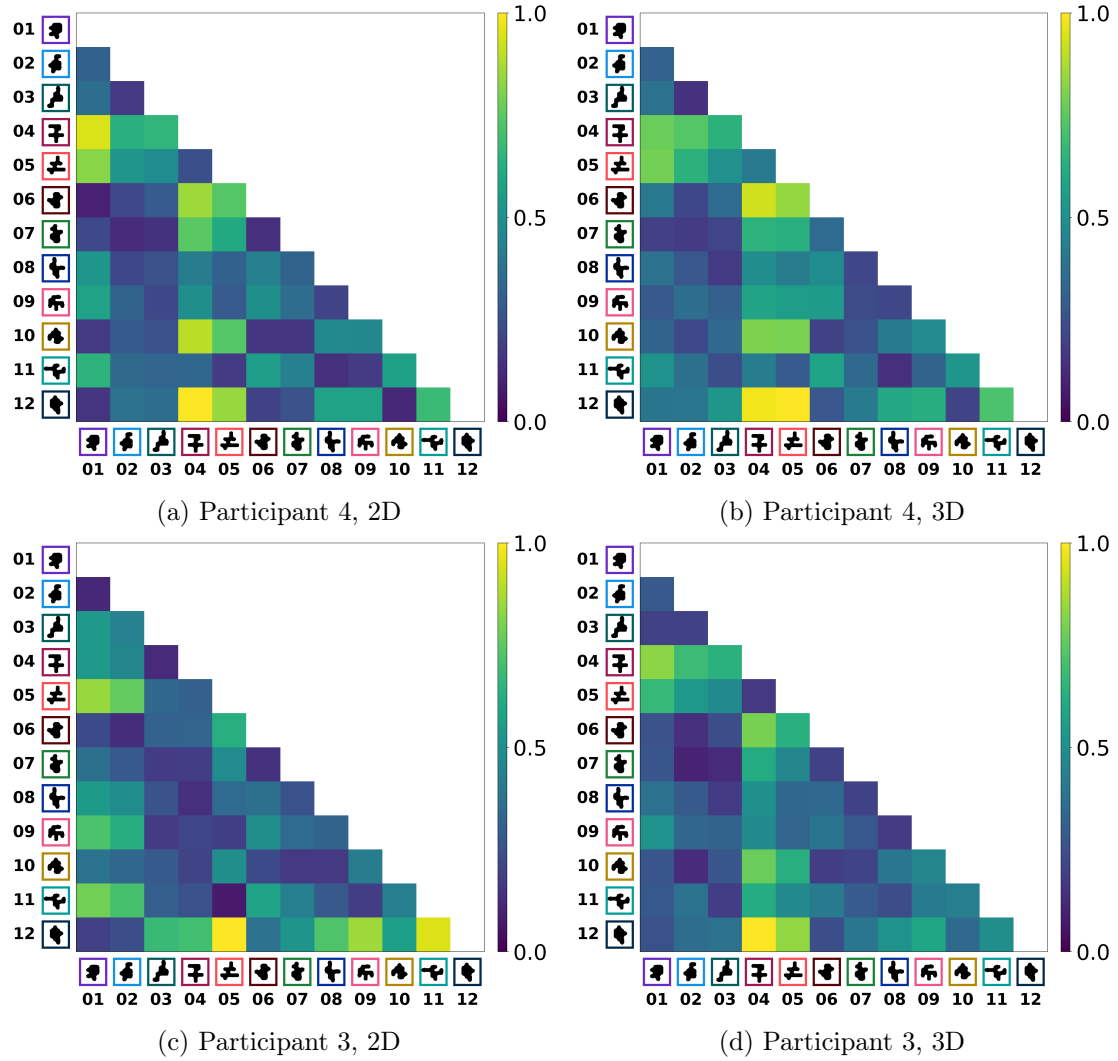


Figure 10.: Representational dissimilarity matrices (RDMs) based on Euclidean distances for two selected illustrative participants in the 2D and 3D conditions. Each matrix shows pairwise dissimilarities between all stimuli, with color indicating the magnitude of dissimilarity.

Using participants' coordinate data, representational dissimilarity matrices (RDMs) were computed for each participant. Overall, the resulting RDMs show substantial variability in arrangement-derived dissimilarity structure. Participants 4 and 3 are shown here as selected illustrative examples with relatively high and lower within-participant cross-dimensional  $\rho$  values, respectively.

To describe within-participant cross-dimensional correspondence, Spearman rank correlations were computed according to Eq. 2.6 using RDMs derived from the 2D ( $d = 2$ )

and 3D ( $d = 3$ ) conditions of the same participant. This measure summarizes similarity in relational rank order independently of absolute distance magnitude. The correlation coefficient  $\rho$  lies in the interval  $[-1, 1]$ , where  $-1$  indicates a perfectly inverted rank ordering,  $0$  indicates no association, and  $1$  indicates a perfectly preserved rank ordering. Participant 4 showed a comparatively high correspondence ( $\rho = 0.838$ ), whereas Participant 3 showed a lower correspondence ( $\rho = 0.367$ ), illustrating descriptive variability in how strongly individual participants preserved their own relational rank ordering across 2D and 3D. Remaining participant-specific overviews are provided in Appendix C, and supplementary similarity diagnostics are summarized in Section D.

## 3.2. Between-Participant Relational and Geometric Structure

### 3.2.1. Between-Participant Consistency

Between-participant consistency was analyzed to assess whether participants externalized similar relational structures when given the same stimuli and task instructions. Higher consistency would indicate a more shared similarity organization, whereas lower consistency would suggest more idiosyncratic use of the arrangement space.

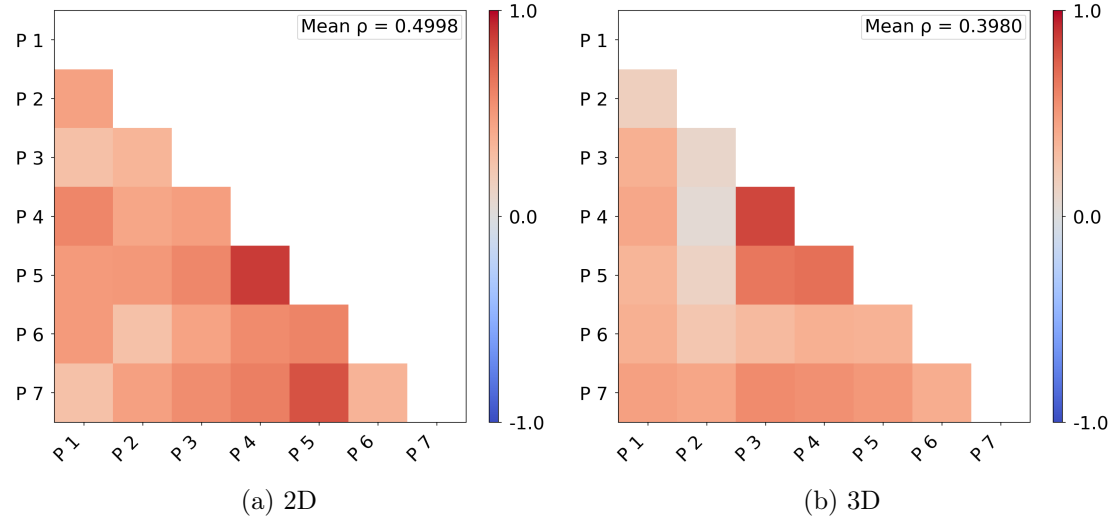


Figure 11.: Between-participant consistency based on Spearman correlations between participant-specific dissimilarity matrices in the 2D and 3D conditions. Each cell represents the pairwise correlation between two participants, with higher values indicating stronger consistency in relational similarity structure.

Figure 11 shows between-participant consistency based on Spearman correlations of participant-specific dissimilarity matrices. For each participant pair, correlations were computed between the vectorized upper-triangular entries of their dissimilarity matrices, capturing consistency in the rank ordering of pairwise stimulus distances. Descriptively, correlation values are higher in the 2D condition (mean  $\rho = 0.500$ ) than in the 3D condition (mean  $\rho = 0.398$ ), indicating stronger between-participant consistency in arrangement-derived relational structure in 2D within this sample. Across participants, correlation values vary in both conditions, but this variability is more pronounced in 3D, where multiple participant pairs show lower correlations. Taken descriptively, the 3D condition therefore shows greater relational heterogeneity across participants.

### 3.2.2. Procrustes Alignment

Procrustes alignment was included as a complementary geometric analysis. While the Spearman-based analysis compares rank-ordered pairwise distances, Procrustes alignment asks whether participants produced similarly shaped configurations after arbitrary differences in position, orientation, reflection, and scale have been removed. The goal is therefore to describe residual coordinate-level shape differences between participant configurations.

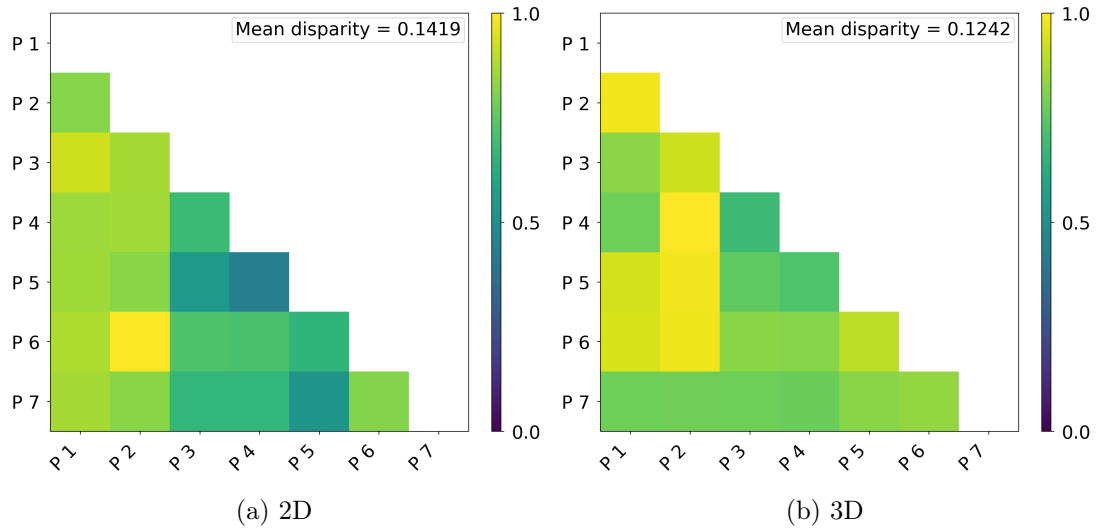


Figure 12.: Pairwise normalized Procrustes-aligned RMSE between participant configurations in the 2D and 3D conditions. Each matrix entry compares participant  $P_i$  with participant  $P_j$ , where  $i$  and  $j$  index participants.

Figure 12 shows pairwise normalized Procrustes-aligned RMSE values for the 2D and 3D conditions, where Procrustes alignment removes differences in position, orientation, and scale so that the remaining RMSE reflects residual differences in configuration shape. For each participant pair, configurations were aligned before computing the remaining geometric difference between them. Averaged across participant pairs, the mean RMSE is slightly higher in 2D ( $0.142 \pm 0.027$ ) than in 3D ( $0.124 \pm 0.014$ ), reported as mean  $\pm$  standard deviation. In the case of a perfect alignment, the residual RMSE would be zero. Values above zero indicate that some differences in the relative arrangement of stimuli remain even after these global transformations have been removed. Thus, this analysis focuses on residual configuration shape rather than on absolute screen position or display scale. Within this normalized Procrustes summary, the 3D configurations therefore show somewhat lower residual coordinate-level discrepancy after alignment. This pattern does not directly contradict the Spearman, Shepard, and kNN analyses, because those measures compare relational distance structures rather than aligned coordinate configurations. Because the Procrustes summaries are computed in spaces with different dimensionality and after normalization, they are treated as a separate geometric description rather than as raw evidence.

### 3.3. Agreement with Leave-One-Out Consensus

The previous between-participant analyses describe how similar participants are to one another, but they do not yet ask how well each individual arrangement matches a shared reference structure. The leave-one-out consensus analysis addresses this question by comparing each participant with a reference computed from all other participants in the same condition. Excluding the evaluated participant avoids circularity: the participant is tested against a group pattern to which they did not contribute. If a condition produces a stable shared similarity structure, participant-specific distances should agree closely with this leave-one-out reference, yielding high Shepard agreement and high kNN overlap. In the opposite case, if arrangements are more idiosyncratic, distances should scatter more strongly around the reference, resulting in lower Shepard agreement and weaker neighborhood preservation.

### 3.3.1. Global Agreement: Shepard Analysis

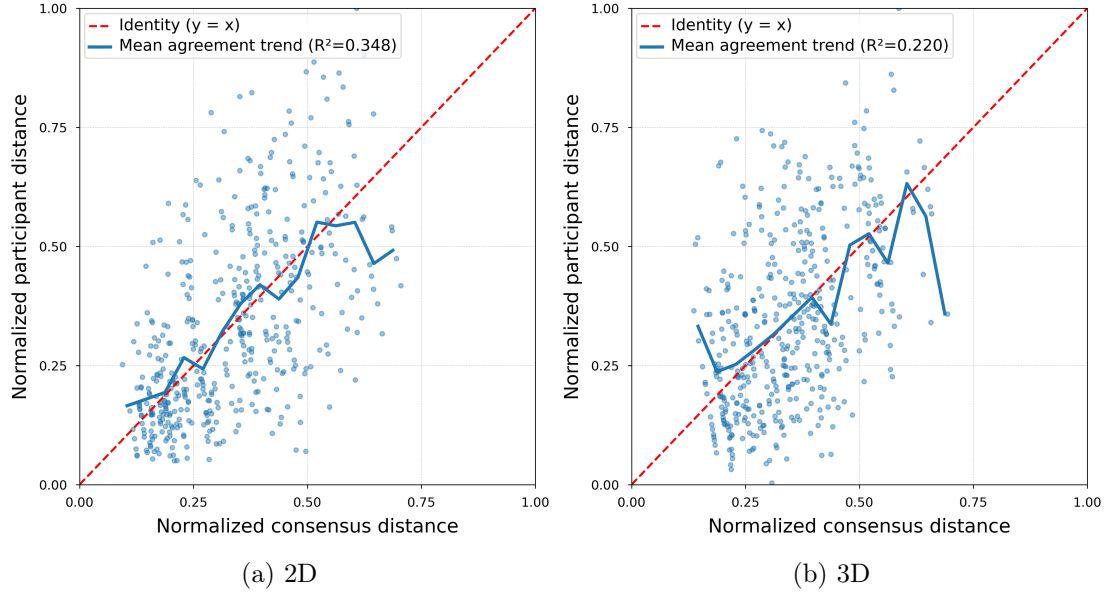


Figure 13.: Each point represents one pooled participant-by-stimulus-pair observation  $(a, i, j)$ , with leave-one-out consensus dissimilarity  $\delta_{ij}^{(d,-a)}$  on the x-axis and arrangement-derived distance  $D_{ij}^{(a,d)}$  on the y-axis. The diagonal denotes perfect agreement with the reference.

The Shepard diagrams plot arrangement-derived distances against leave-one-out consensus dissimilarities, thereby assessing how well participant-specific configurations preserve the shared relational structure estimated from the other participants in the same condition. The reported condition-level coefficients correspond to the pooled coefficient of determination defined in Eq. (2.11), summarizing the overall agreement between arrangement-derived and reference distances across all participants and stimulus pairs within each condition. The diagrams indicate a moderate correspondence between reference dissimilarities and arrangement-derived distances in both conditions. Under this descriptive aggregation, the 2D condition shows a slightly higher pooled coefficient of determination ( $R_{2,\text{pooled}}^2 = 0.348$ ) than the 3D condition ( $R_{3,\text{pooled}}^2 = 0.220$ ), indicating somewhat stronger agreement with the leave-one-out consensus reference in the 2D arrangements. By contrast, the 3D condition shows slightly greater dispersion around the line of perfect agreement. Because the reference is sample-derived and the pooled stimulus-pair observations are not independent, this result is interpreted as a descriptive agreement-to-consensus pattern rather than as an inferential accuracy estimate.



### 3.3.2. Local Agreement: k-Nearest Neighbor Preservation

The Shepard analysis summarizes global agreement across all stimulus-pair distances, whereas the k-nearest-neighbor analysis tests local structure by asking whether each stimulus has the same close neighbors in an individual arrangement and in the leave-one-out consensus. If a condition preserves fine-grained local similarity relations, neighborhood overlap should be high, especially for small  $k$ ; if local neighborhoods are unstable or participant-specific, overlap should be lower even when broader distance patterns still show some agreement.

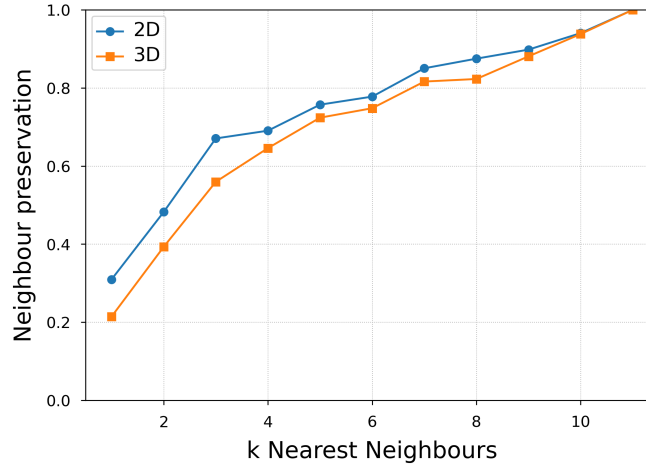


Figure 14.: k-nearest-neighbor (kNN) preservation curves for the 2D and 3D conditions. The x-axis shows neighborhood size  $k$ , and the y-axis shows average neighbor overlap with the leave-one-out consensus reference. Higher values indicate stronger local agreement.

Figure 14 shows the condition-level preservation curves for both task conditions, with each point corresponding to  $\overline{\text{kNN}}_d(k)$  as defined in Eq. (2.13). In the small-neighborhood regime ( $k = 1\text{--}3$ ), the 2D condition exhibits slightly higher overlap values, indicating somewhat stronger local agreement with the leave-one-out consensus reference for the most immediate stimulus relations, whereas both conditions converge for larger neighborhoods ( $k \geq 7$ ). This convergence is expected because large neighborhoods include an increasing share of the small stimulus set and therefore become less sensitive to local differences. Because the reference is itself a leave-one-out between-participant consensus, these curves are interpreted here as descriptive agreement-to-consensus summaries rather than as independent reliability estimates.

## 3.4. Interface-Axis Use

### 3.4.1. Axis Variance Ratios

Axis-variance analysis was used to describe how participants distributed their placements across the available interface coordinates. Balanced variance ratios would indicate that the available axes were used relatively evenly, whereas strong concentration on one axis would indicate uneven use of the recorded interface dimensions.

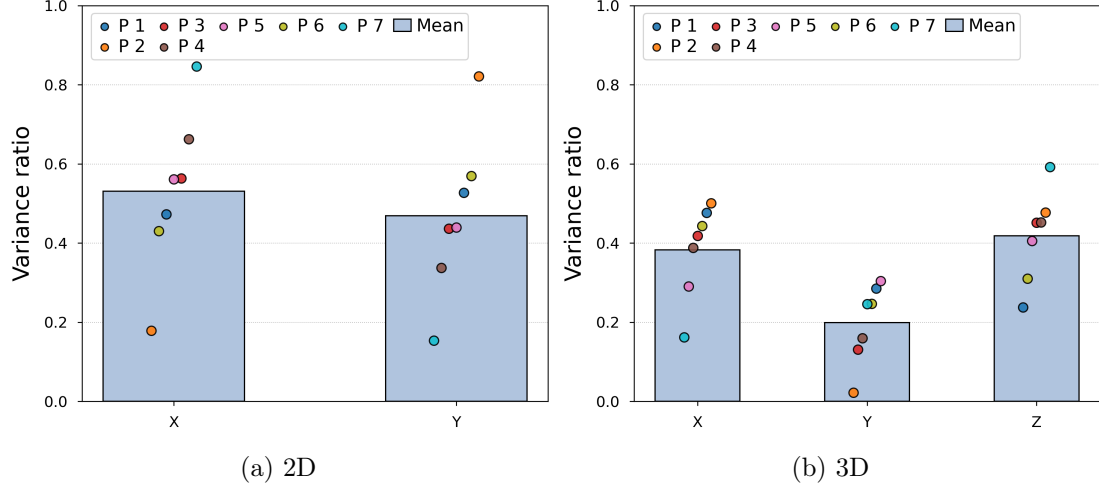


Figure 15.: Axis-wise variance ratios for submitted configurations in the 2D ( $d = 2$ ) and 3D ( $d = 3$ ) conditions. Bars show the mean participant-wise relative contribution of each recorded interface axis, computed by first normalizing each participant’s axis variances and then averaging across participants to obtain  $\bar{r}_{k,d}$ . More balanced ratios indicate a more even distribution within the logged interface frame.

In the 2D condition, the mean participant-wise variance ratios are distributed relatively evenly across the two recorded planar coordinates, with approximately 0.53 on the  $x$ -axis and 0.47 on the  $y$ -axis. In contrast, the 3D condition shows a more uneven distribution in the recorded interface frame, with mean participant-wise variance ratios of approximately 0.38 ( $x$ ), 0.20 ( $y$ ), and 0.42 ( $z$ ). Descriptively, this pattern indicates that the submitted 3D configurations are not distributed uniformly across the recorded interface coordinates. This summary is useful for describing how participants used the available placement axes, because it is tied to the raw interface frame, it is not evidence for psychologically privileged latent axes and is not directly comparable to the other consistency measures.

### 3.5. Results of the Debriefing Survey

Table 2.: Participant responses grouped by question (Q1–Q4)

| Q1. How did you do the task? Did you follow any strategy?                             |                                                         |
|---------------------------------------------------------------------------------------|---------------------------------------------------------|
| Participant                                                                           | Answer                                                  |
| P1                                                                                    | Shape-based grouping (compressed vs. stretched forms).  |
| P2                                                                                    | Grouped by broad visual categories.                     |
| P3                                                                                    | Grouping by convexity and elongation.                   |
| P4                                                                                    | Iterative, adjustment-based placement.                  |
| P5                                                                                    | More global placement with limited grouping.            |
| P6                                                                                    | Mixed grouping and global strategy.                     |
| P7                                                                                    | Grouping based on similarity features.                  |
| Q2. Did you do things differently between the 2D and 3D conditions?                   |                                                         |
| Participant                                                                           | Answer                                                  |
| P1                                                                                    | Similar strategy across conditions.                     |
| P2                                                                                    | Used 3D for better separation.                          |
| P3                                                                                    | More categorization in 3D.                              |
| P4                                                                                    | Used 3D for spatial differentiation.                    |
| P5                                                                                    | 3D enabled more differentiation.                        |
| P6                                                                                    | Used 3D selectively.                                    |
| P7                                                                                    | 3D allowed better separation but was harder to control. |
| Q3. Did the additional coordinate feel meaningful and usable, or redundant/confusing? |                                                         |
| Participant                                                                           | Answer                                                  |
| P1                                                                                    | 3D perceived as largely unnecessary.                    |
| P2                                                                                    | 3D meaningful and useful.                               |
| P3                                                                                    | 3D useful but slightly challenging.                     |
| P4                                                                                    | 3D useful for expressing distances.                     |
| P5                                                                                    | 3D meaningful and versatile.                            |
| P6                                                                                    | 3D partly meaningful.                                   |
| P7                                                                                    | 3D somewhat confusing but not redundant.                |
| Q4. Did you use the axes? How, and did you feel uncertain about them?                 |                                                         |
| Participant                                                                           | Answer                                                  |
| P1                                                                                    | Explicit axis mapping.                                  |
| P2                                                                                    | Axes used implicitly.                                   |
| P3                                                                                    | Axes emerged over time.                                 |
| P4                                                                                    | Axes mostly ignored.                                    |
| P5                                                                                    | Explicit axis use.                                      |
| P6                                                                                    | Partly explicit axis use.                               |
| P7                                                                                    | Partial axis use.                                       |

Table 3.: Participant responses grouped by question (Q5–Q8)

---

**Q5.** What do you think about the interface?

---

**Participant Answer**

---

|    |                                                            |
|----|------------------------------------------------------------|
| P1 | 3D interaction overcomplicated.                            |
| P2 | Interface clear.                                           |
| P3 | Interface clear.                                           |
| P4 | Interface clear.                                           |
| P5 | Interface clear.                                           |
| P6 | Interface clear with slightly higher complexity in 3D.     |
| P7 | Interface clear, but 3D placement was harder to interpret. |

---

**Q6.** Did the order of objects influence your perception?

---

**Participant Answer**

---

|    |                          |
|----|--------------------------|
| P1 | No order effect.         |
| P2 | No order effect.         |
| P3 | No influence.            |
| P4 | Minimal order influence. |
| P5 | No order effect.         |
| P6 | No order effect.         |
| P7 | No order effect.         |

---

**Q7.** Which condition was more mentally demanding, and why?

---

**Participant Answer**

---

|    |                                      |
|----|--------------------------------------|
| P1 | 3D more demanding.                   |
| P2 | 3D more demanding.                   |
| P3 | 3D more demanding.                   |
| P4 | 3D more demanding.                   |
| P5 | 3D more demanding but engaging.      |
| P6 | 3D not demanding.                    |
| P7 | 3D more demanding due to navigation. |

---

**Q8.** What would you change to better express similarities?

---

**Participant Answer**

---

|    |                                       |
|----|---------------------------------------|
| P1 | No major changes.                     |
| P2 | Suggested more objects.               |
| P3 | Suggested a more structured strategy. |
| P4 | No major changes.                     |
| P5 | Suggested more diverse stimuli.       |
| P6 | Suggested minor improvements.         |
| P7 | Suggested additional visual aids.     |

---

To complement the quantitative evaluation, participants also completed semi-structured debriefing interviews after the experiment. The responses are summarized here descriptively to provide contextual information about task strategies, subjective perceptions, and interaction behaviors underlying the observed spatial arrangements. Whereas the quantitative metrics (e.g., Procrustes-aligned RMSE and kNN preservation) capture structural properties of the arrangement-derived dissimilarity structures, they do not directly reveal how participants approached the task, interpreted the available degrees of freedom, or responded to interaction constraints.

For this purpose, participants answered a common set of prompts covering strategy formation, the perceived usefulness of the additional coordinate, axis interpretation, interface usability, and cognitive load. These questions were intended to probe differences between the 2D and 3D conditions systematically and to identify potential sources of variability and inconsistency across participants.

The responses were condensed into short paraphrased summaries to facilitate comparison across individuals and conditions while preserving the main points raised by each participant. No formal coding procedure was applied to these interviews; accordingly, the material is used here as contextual description rather than as an independent source of qualitative evidence. The tables summarize the debriefing questions used in the study and provide a compact overview of participant responses.

Overall, participants' perceptions of the additional coordinate were mixed: some described it as useful and expressive, whereas others found it harder to control or navigate. More specifically, several responses suggest that 3D was experienced as beneficial when participants wanted to separate similar stimuli more clearly or distribute groups more flexibly, but less helpful when  $z$ -coordinate placement, camera rotation, or viewpoint-dependent monitoring made configurations harder to evaluate. Because these interview notes are compact paraphrases rather than formally coded qualitative data, they are interpreted only as contextual observations, and some responses suggest a trade-off between added expressive flexibility in 3D and increased monitoring and control demands that is compatible with the quantitative pattern of greater variability in 3D. Read descriptively, the usefulness of the additional coordinate appears to have depended less on a uniform benefit than on participants' individual strategies and control preferences.

## 4. Discussion

### 4.1. Main Findings

This study examined whether the dimensionality of the placement interface changes the similarity structure externalized in a single-trial iMDS task. The main result is a difference in consistency rather than a simple advantage of either condition. The 2D condition shows more consistent relational structure across participants, whereas the 3D condition shows more variable relational patterns and more uneven use of the recorded interface axes.

The between-participant results support this interpretation. Participant RDMs are more strongly aligned in 2D than in 3D, with higher mean Spearman consistency in 2D. The Procrustes summary points in a different direction, because the aligned coordinate-level RMSE is slightly lower in 3D. This does not overturn the relational results. It shows that aligned configuration shape and rank-ordered dissimilarity structure capture different aspects of the data.

The consensus-based analyses show the same overall tendency. In the Shepard analysis, both conditions show structured agreement with the leave-one-out consensus reference, but this agreement is lower in 3D. The kNN results add that the difference is most visible for small neighborhoods, where 2D preserves local consensus relations more strongly. For larger neighborhoods the curves converge, which is expected with only twelve stimuli. The axis-variance results further clarify the 3D pattern. In 2D, variance is distributed almost evenly across the two recorded coordinates. In 3D, variance is concentrated more strongly on the  $x$ - and  $z$ -axes than on the  $y$ -axis. This indicates uneven use of axes, but it should not be interpreted as psychological evidence.

The findings support a cautious interpretation: adding a third placement coordinate increased expressive freedom, but it did not make the similarity structure more shared across participants. Several participants described the additional coordinate as useful, but also more demanding. Thus, the 3D condition appears to have made individual strategies more visible rather than producing a single, more consistent relational representation.

## 4.2. Relation to Previous Work

The findings extend earlier work on multidimensional scaling and spatial arrangement methods by focusing on the interaction space itself. Previous studies show that spatial arrangements can recover meaningful similarity structure efficiently (Goldstone, 1994a; Hout et al., 2013; Richie et al., 2020). The present results are compatible with that view because both conditions produced structured RDMS. However, they also show that adding an interaction dimension does not automatically increase shared structure across participants.

This distinction is important for interpreting the relation to inverse MDS. Multi-arrangement iMDS combines several two-dimensional arrangements to estimate a richer dissimilarity structure (Kriegeskorte and Mur, 2012). The present study instead compared one 2D arrangement with one 3D arrangement. The lower consensus-related agreement in 3D should therefore not be read as evidence against iMDS or SpAM. It suggests that a single 3D arrangement and repeated 2D arrangements solve the dimensionality problem in different ways: one adds placement freedom within a trial, whereas the other adds repeated evidence across trials.

The results also fit previous cautions that spatial arrangement data can depend on task constraints, display geometry, and participant strategies (Verheyen et al., 2016). In this study, 3D interaction offered more degrees of freedom, but it also introduced additional control and monitoring demands. This trade-off provides a plausible explanation for why 3D was often experienced as expressive while still producing lower consensus-related agreement.

## 4.3. Limitations

### Exploratory sample

The participant sample is small, and the analyses are descriptive. Several metrics also use pairwise participant relations or pooled stimulus-pair observations, so they should not be treated as independent inferential observations. The reported patterns should therefore be read as observations within this dataset rather than as population-level condition effects.

### **Interindividual strategies**

Spatial arrangement tasks depend on subjective judgments and strategy choices. Differences between participants may reflect stable perceptual representations, task-specific strategies, or both. The present data do not separate these possibilities conclusively.

### **Interaction complexity**

The 2D and 3D conditions differ not only in dimensionality. The 3D condition also required camera control, depth monitoring, and more complex spatial reasoning. Part of the increased variability in 3D may therefore reflect interaction difficulty rather than representational differences alone.

### **Measurement scope**

The relational and geometric summaries emphasize different aspects of the arrangements. RDM-based measures capture pairwise dissimilarity structure, whereas aligned coordinate summaries describe residual shape differences after alignment. Neither perspective fully captures all aspects of how participants used the workspace.

### **Stimulus set**

The stimulus set contained only twelve items. This limits the complexity of possible neighborhood structures and makes large-neighborhood kNN values less diagnostic. Larger stimulus sets may produce more stable and more informative similarity representations.

## **4.4. Open Questions and Future Work**

Several questions remain open. First, the present design cannot fully separate the effect of interaction dimensionality from the effect of interaction complexity. The 3D condition provided an additional coordinate, but it also required camera control,  $z$ -coordinate monitoring, and more complex spatial reasoning. Future studies could compare several interface variants, for example a 3D condition with stronger visual aids, fixed canonical views, or explicit  $z$ -coordinate cues, to test whether lower agreement in 3D is caused by the additional configuration freedom itself or by the difficulty of controlling the interface.



Second, future work should compare single-trial 3D arrangements directly with established multi-arrangement iMDS procedures. The present study asks whether one richer placement space changes the resulting similarity representation, whereas multi-arrangement iMDS estimates dissimilarity structure by combining multiple constrained arrangements (Kriegeskorte and Mur, 2012). A direct comparison between single 2D, single 3D, and repeated 2D arrangements would clarify whether 3D interaction can replace, complement, or merely alter the information gained from multiple 2D trials.

Third, the present study used a small stimulus set and a small exploratory participant sample. Larger stimulus sets would make it possible to test whether 3D interaction becomes more beneficial when the similarity relations are too complex or crowded for a planar layout. Larger samples would also allow formal reliability analyses, preregistered hypotheses, and inferential comparisons instead of the descriptive summaries used here. Such follow-up work could also vary the stimulus domain itself, for example by comparing simple perceptual silhouettes with richer object categories or semantic materials, to test whether the usefulness of an additional recorded interaction coordinate depends on the complexity and interpretability of the underlying similarity space.

Finally, future research could combine RDM-based analyses with a more systematic qualitative coding of participant strategies. The debriefing responses suggest that participants differed in whether they used axes explicitly, relied on local neighborhoods, formed clusters, or treated the  $z$  coordinate as a separation axis. A formal coding scheme, combined with richer logged interaction data such as movement trajectories and revision patterns, could test whether particular strategies explain why some 3D arrangements remain close to the consensus while others diverge more strongly. More detailed interaction logs could also reveal whether participants initially explore the  $z$  coordinate and later collapse back toward a planar solution, or whether the additional coordinate is used consistently throughout the trial. This would help distinguish stable representational use of 3D space from temporary interface exploration.

## 4.5. Conclusion

The present study suggests that interaction dimensionality changes how similarity structure is expressed in this iMDS spatial arrangement task. Within this exploratory sample, the 2D condition is associated with higher between-participant consistency, whereas the 3D condition is associated with more heterogeneous relational patterns and interface-axis use.

Relative to the leave-one-out consensus reference used here, both conditions show structured but imperfect agreement, with lower consensus-related agreement in 3D. Increasing dimensionality therefore does not simply improve or impair performance; in this dataset, it changes the descriptive balance between tighter between-participant consistency and greater heterogeneity in relational and interface-axis use patterns. Future work should examine how interaction complexity, participant strategy, stimulus set size, and the relation between relational and geometric measures shape this pattern.

# Appendices

This appendix provides supplementary material supporting the analyses presented in the main text. It includes implementation details, additional resources, and visualization specifications to ensure transparency and reproducibility of the results.

## A. Code Availability

The full analysis and visualization pipeline is publicly available at: [GitHub repository](#). The repository contains all scripts required to reproduce the reported results, including data processing, RDM computation, and visualization.

## B. Tutorial Video

A tutorial video demonstrating the experimental setup and interaction procedure is available upon request.

## C. Trial Data

Each participant is documented on two pages. Across these pages, all 3D analyses are shown on the left and all 2D analyses on the right. The pages include rounded coordinate tables, spatial arrangements, representational dissimilarity matrices, Shepard plots, and axis-variance plots; a cross-dimensional RDM comparison is shown below. All coordinate tables are rounded to three decimals for readability, while the quantitative analyses in the main text use the recorded interface coordinates before table formatting.

## Participant 1

| Condition: 3D |        |        |        |
|---------------|--------|--------|--------|
| Stimulus      | x      | y      | z      |
| 01            | 0.014  | -0.720 | -0.280 |
| 02            | 0.281  | 0.000  | -0.120 |
| 03            | -0.258 | 0.600  | -0.495 |
| 04            | 0.900  | 0.000  | 0.444  |
| 05            | 1.000  | 0.000  | 0.416  |
| 06            | 0.000  | 0.300  | -0.320 |
| 07            | 0.478  | 0.000  | 0.135  |
| 08            | 0.487  | 0.000  | 0.143  |
| 09            | 0.638  | -0.060 | 0.168  |
| 10            | 0.076  | 0.000  | -0.237 |
| 11            | 1.000  | -0.240 | 0.101  |
| 12            | 0.134  | -0.420 | -0.215 |

| Condition: 2D |        |        |       |
|---------------|--------|--------|-------|
| Stimulus      | x      | y      | z     |
| 01            | -0.618 | -0.855 | 0.000 |
| 02            | -0.087 | 0.046  | 0.000 |
| 03            | -0.157 | 0.774  | 0.000 |
| 04            | 0.971  | -0.687 | 0.000 |
| 05            | 0.757  | -0.589 | 0.000 |
| 06            | -0.165 | -0.261 | 0.000 |
| 07            | -0.058 | 0.284  | 0.000 |
| 08            | -0.073 | 0.481  | 0.000 |
| 09            | 0.597  | -0.478 | 0.000 |
| 10            | -0.275 | -0.528 | 0.000 |
| 11            | 0.438  | -0.200 | 0.000 |
| 12            | -0.415 | -0.748 | 0.000 |

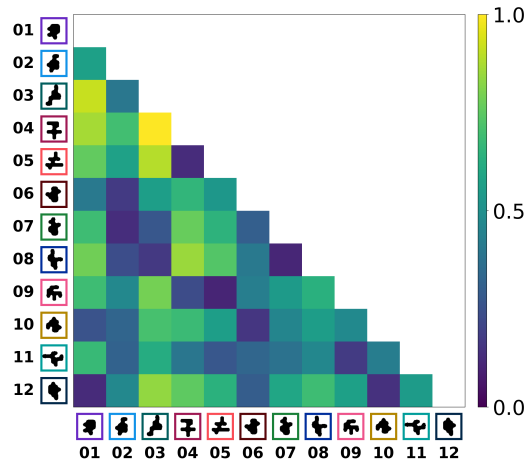
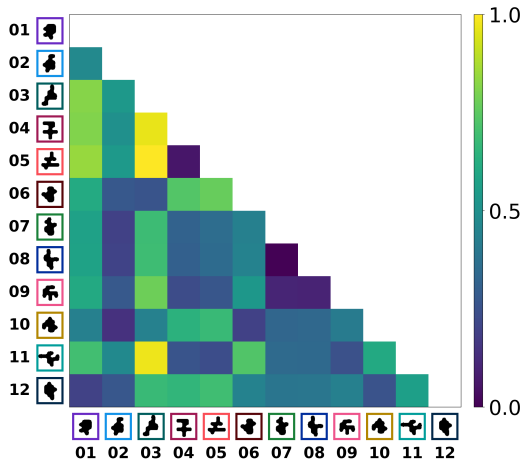
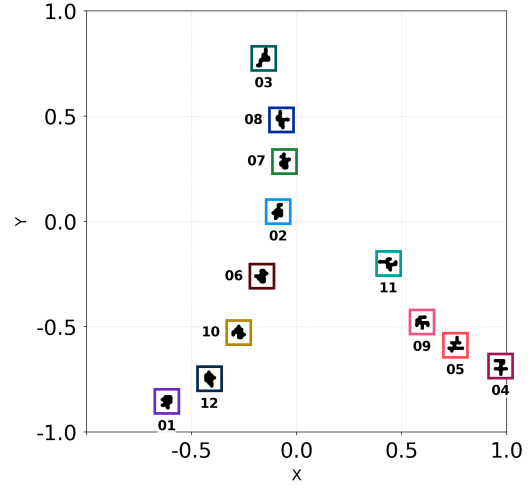
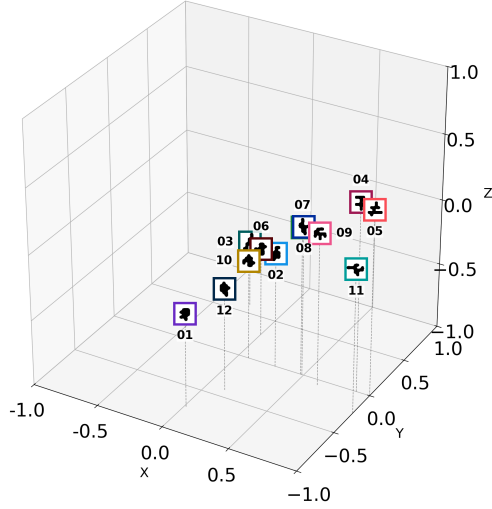
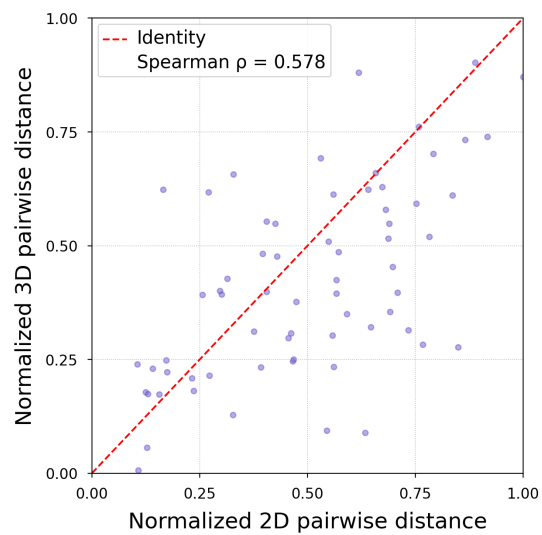
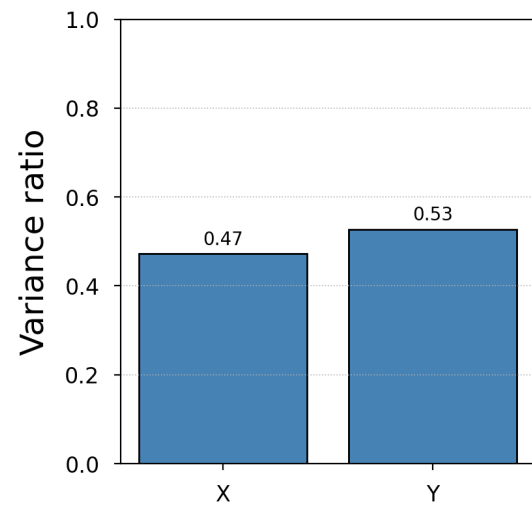
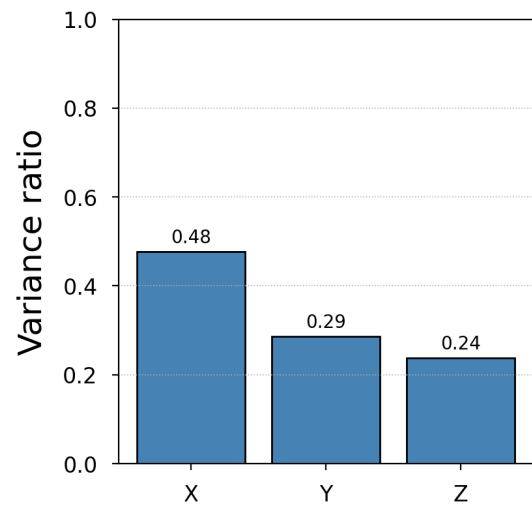
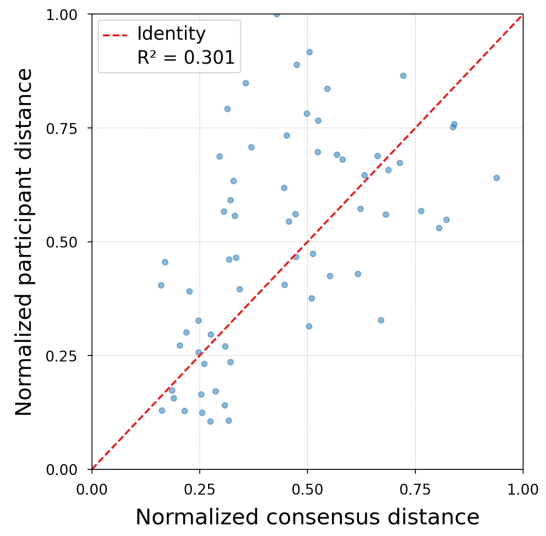
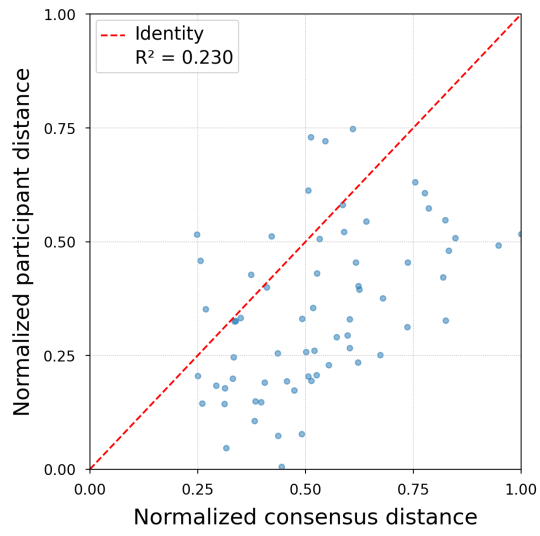


Table 4.: Participant 1: coordinate tables, arrangements, and RDMs.



## Participant 2

| Condition: 3D |        |        |        |  |
|---------------|--------|--------|--------|--|
| Stimulus      | x      | y      | z      |  |
| 01            | 0.101  | 0.000  | 0.029  |  |
| 02            | 0.037  | 0.022  | 0.253  |  |
| 03            | 0.942  | -0.036 | 1.000  |  |
| 04            | 0.614  | 0.000  | -0.554 |  |
| 05            | 0.441  | -0.147 | -0.924 |  |
| 06            | -0.229 | -0.113 | 0.252  |  |
| 07            | -1.000 | 0.000  | -0.293 |  |
| 08            | 0.978  | -0.059 | 0.609  |  |
| 09            | 0.728  | -0.523 | -1.000 |  |
| 10            | -1.000 | 0.000  | 0.019  |  |
| 11            | 0.735  | 0.000  | -1.000 |  |
| 12            | 1.000  | -0.028 | 0.811  |  |

| Condition: 2D |       |        |       |  |
|---------------|-------|--------|-------|--|
| Stimulus      | x     | y      | z     |  |
| 01            | 0.262 | 0.133  | 0.000 |  |
| 02            | 1.000 | 0.123  | 0.000 |  |
| 03            | 0.665 | 0.563  | 0.000 |  |
| 04            | 0.826 | -0.452 | 0.000 |  |
| 05            | 1.000 | -0.459 | 0.000 |  |
| 06            | 0.460 | 0.126  | 0.000 |  |
| 07            | 0.813 | 0.129  | 0.000 |  |
| 08            | 0.514 | 0.563  | 0.000 |  |
| 09            | 0.820 | -0.815 | 0.000 |  |
| 10            | 0.628 | 0.139  | 0.000 |  |
| 11            | 1.000 | -0.825 | 0.000 |  |
| 12            | 0.840 | 0.569  | 0.000 |  |

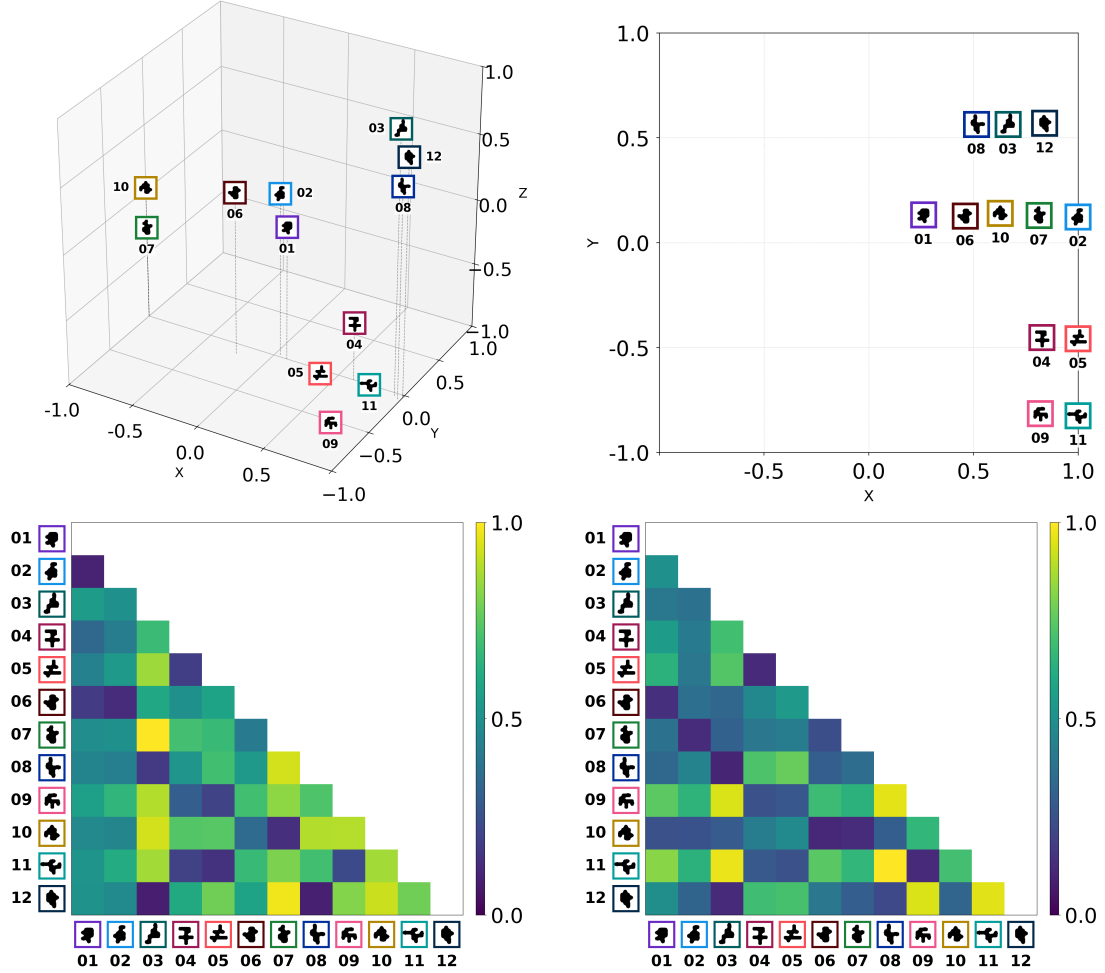
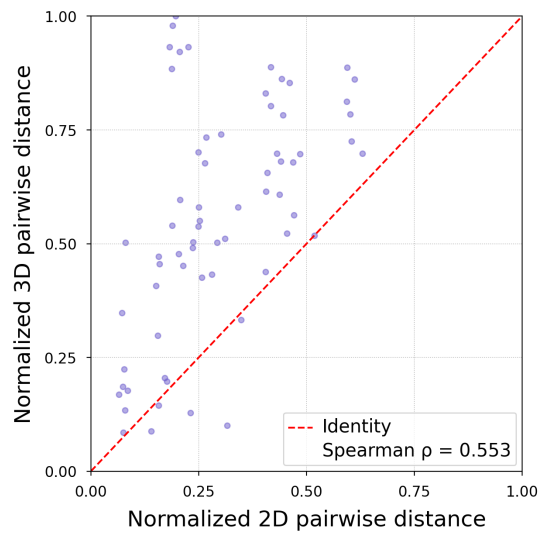
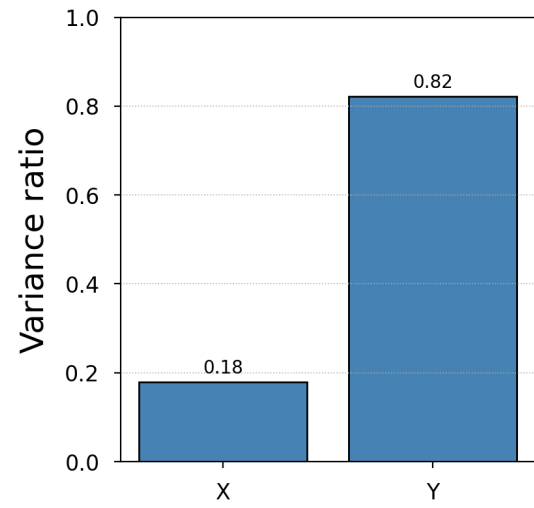
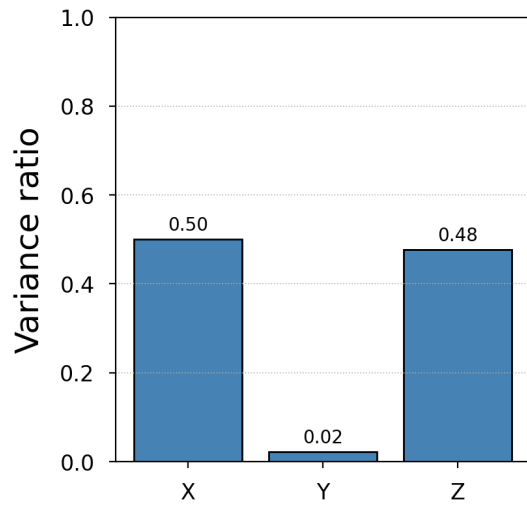
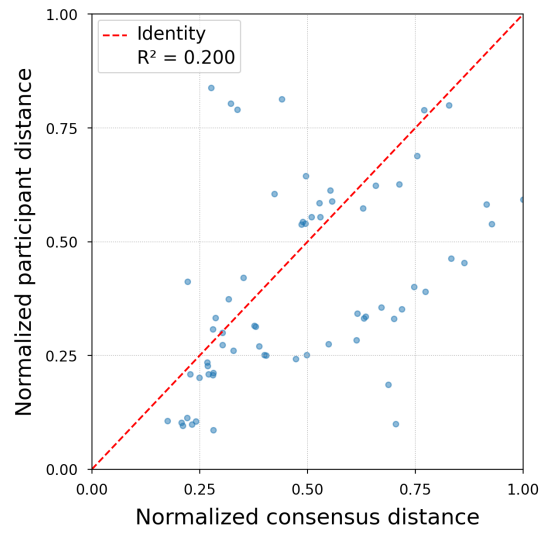
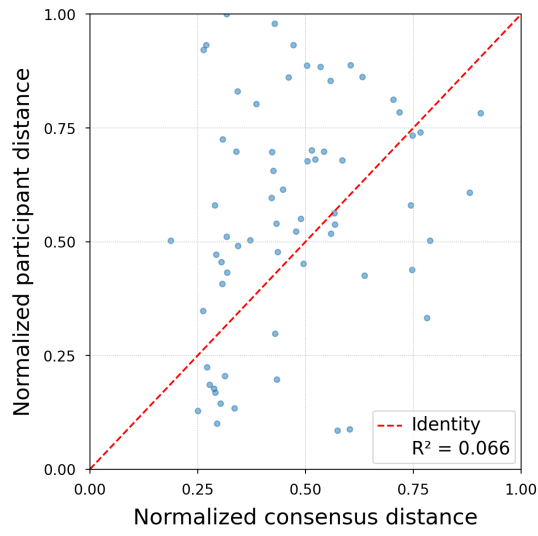


Table 5.: Participant 2: coordinate tables, arrangements, and RDMs.



### Participant 3

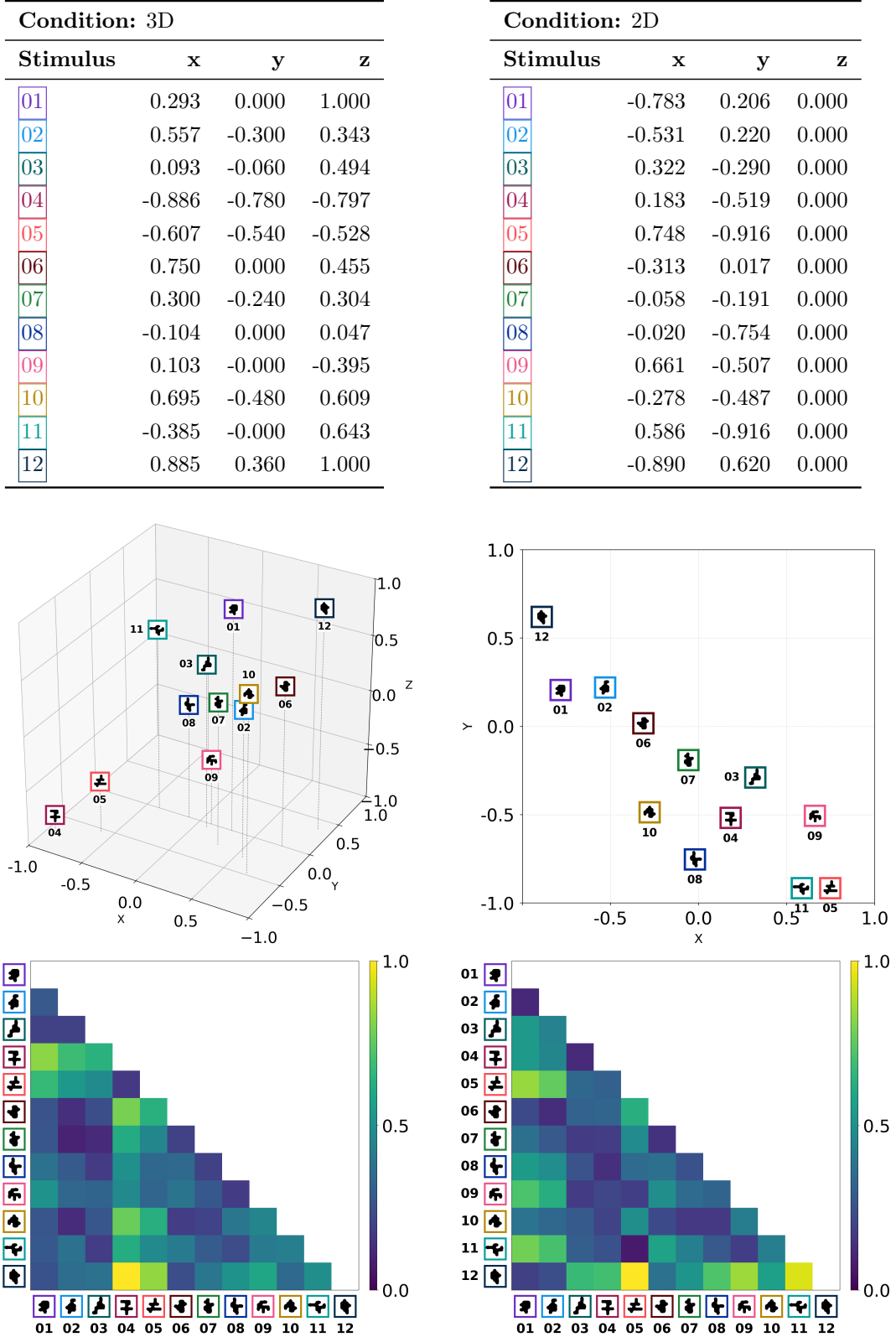
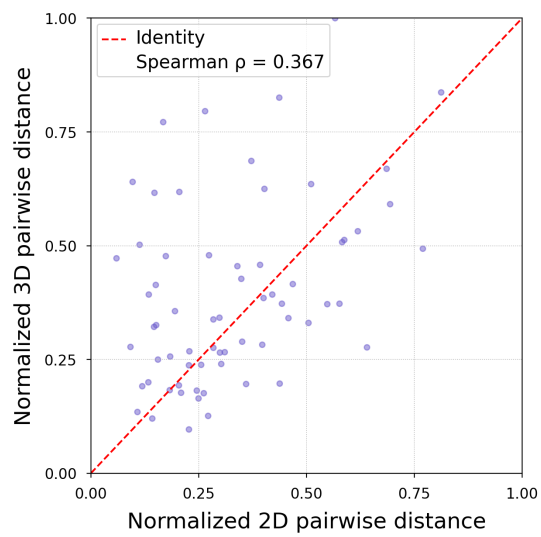
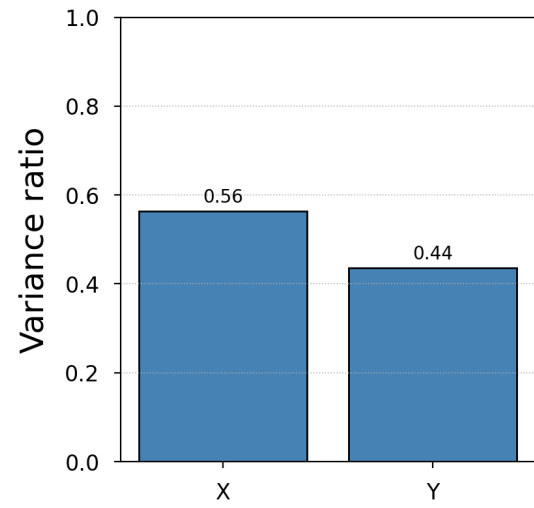
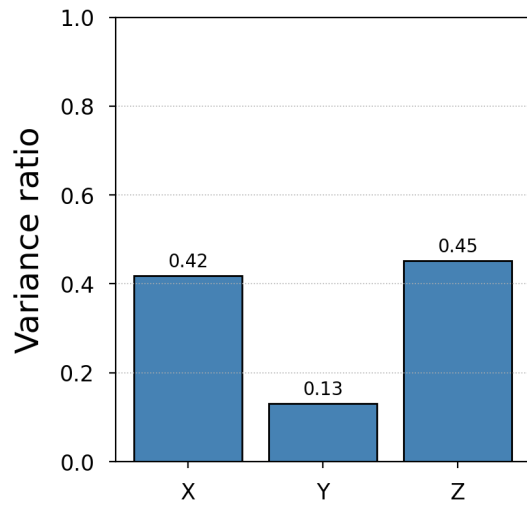
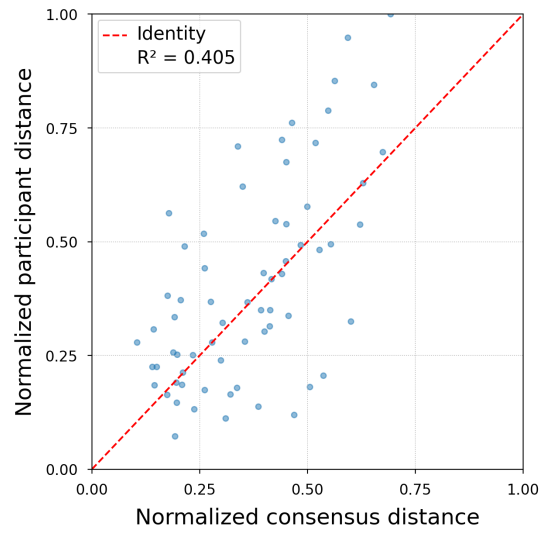
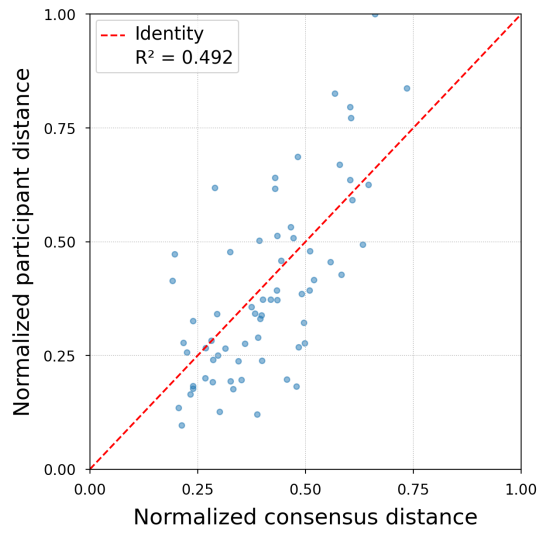


Table 6.: Participant 3: coordinate tables, arrangements, and RDMs.





## Participant 4

| Condition: 3D |        |        |        |
|---------------|--------|--------|--------|
| Stimulus      | x      | y      | z      |
| 01            | -0.216 | 0.000  | -0.563 |
| 02            | 0.032  | -0.240 | -0.082 |
| 03            | -0.163 | -0.240 | 0.099  |
| 04            | -0.671 | 0.720  | 0.618  |
| 05            | -0.697 | 0.000  | 0.843  |
| 06            | 0.379  | -0.360 | -0.255 |
| 07            | -0.164 | 0.000  | -0.213 |
| 08            | -0.365 | -0.000 | 0.130  |
| 09            | -0.591 | 0.000  | -0.202 |
| 10            | 0.309  | 0.000  | -0.269 |
| 11            | -0.430 | 0.000  | 0.372  |
| 12            | 0.510  | 0.000  | -0.592 |

| Condition: 2D |        |        |       |
|---------------|--------|--------|-------|
| Stimulus      | x      | y      | z     |
| 01            | 1.000  | 0.391  | 0.000 |
| 02            | 0.406  | 0.006  | 0.000 |
| 03            | 0.180  | 0.307  | 0.000 |
| 04            | -0.742 | -0.881 | 0.000 |
| 05            | -0.742 | -0.319 | 0.000 |
| 06            | 0.832  | 0.273  | 0.000 |
| 07            | 0.513  | 0.273  | 0.000 |
| 08            | -0.038 | -0.220 | 0.000 |
| 09            | -0.302 | 0.171  | 0.000 |
| 10            | 0.673  | 0.600  | 0.000 |
| 11            | -0.351 | -0.220 | 0.000 |
| 12            | 0.896  | 0.716  | 0.000 |

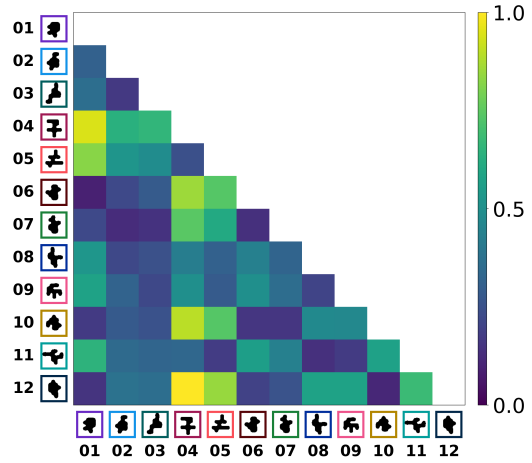
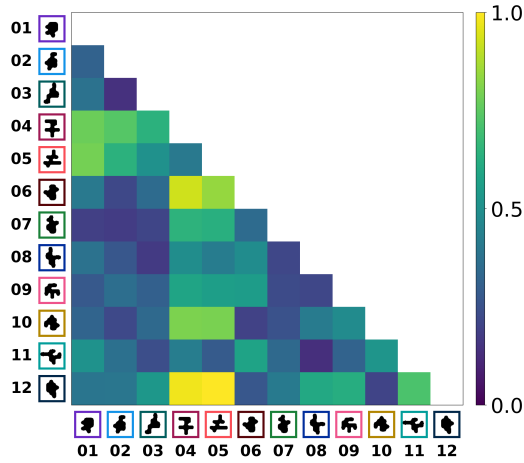
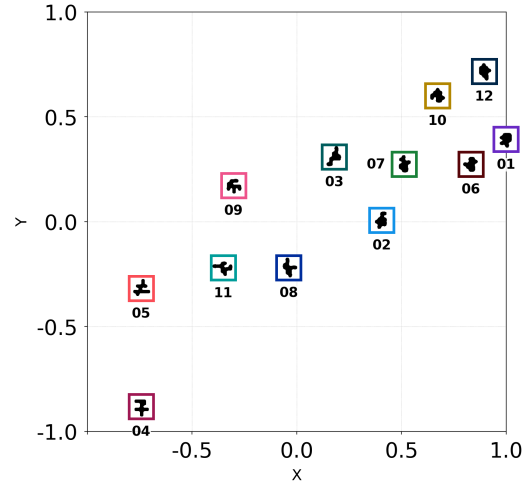
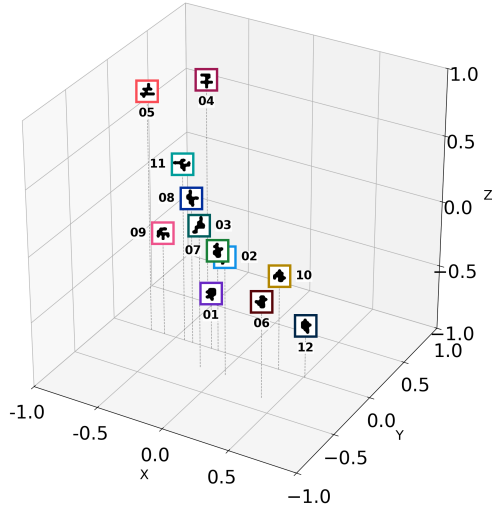
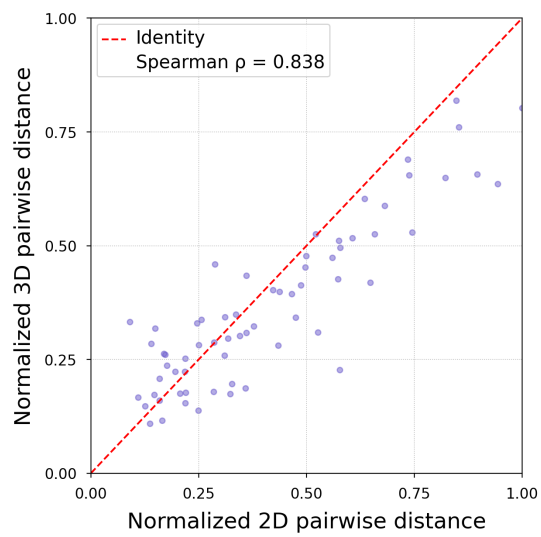
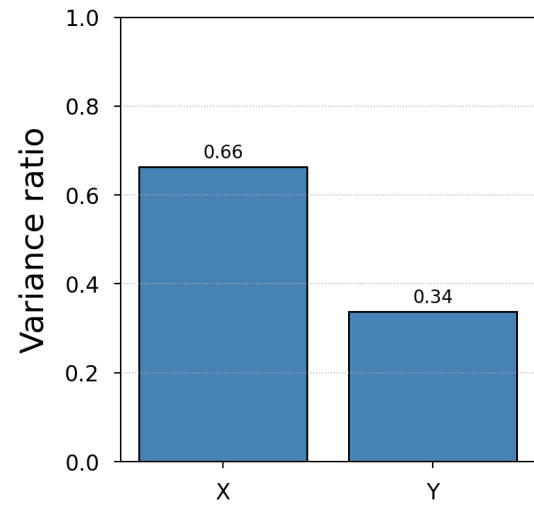
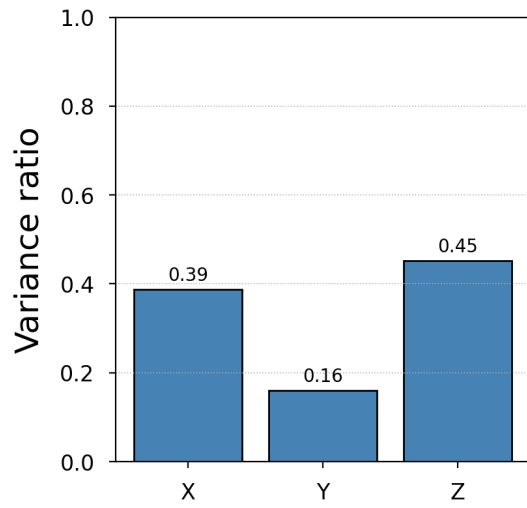
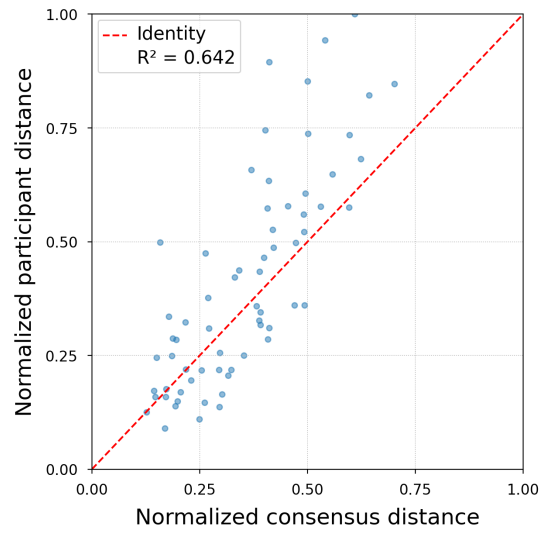
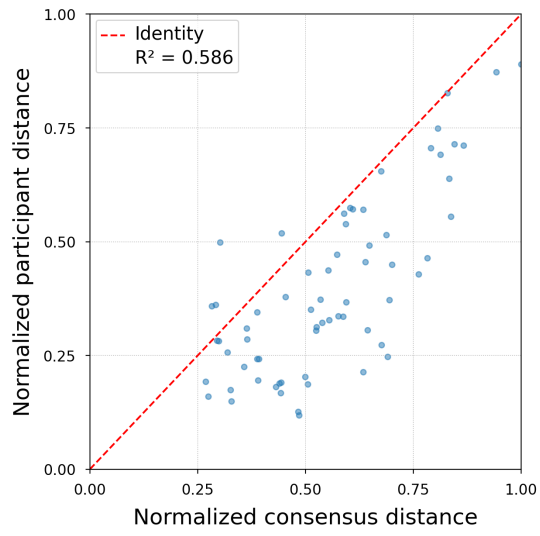


Table 7.: Participant 4: coordinate tables, arrangements, and RDMs.



# Participant 5

| Condition: 3D |        |        |        |
|---------------|--------|--------|--------|
| Stimulus      | x      | y      | z      |
| 01            | -0.073 | 0.760  | 0.060  |
| 02            | -0.170 | 0.240  | 0.377  |
| 03            | 0.409  | 0.000  | -0.486 |
| 04            | 1.000  | -0.900 | -0.768 |
| 05            | 0.878  | -1.000 | 0.846  |
| 06            | -0.738 | 0.420  | 0.234  |
| 07            | 0.060  | -0.380 | -0.067 |
| 08            | -0.561 | -0.120 | 0.864  |
| 09            | -0.092 | -0.840 | 0.922  |
| 10            | -0.518 | 0.000  | -1.000 |
| 11            | 0.162  | -0.540 | 0.649  |
| 12            | -1.000 | 0.840  | -1.000 |

| Condition: 2D |        |        |       |
|---------------|--------|--------|-------|
| Stimulus      | x      | y      | z     |
| 01            | -0.435 | 0.629  | 0.000 |
| 02            | -0.217 | 0.078  | 0.000 |
| 03            | 0.104  | 0.113  | 0.000 |
| 04            | 0.905  | -0.476 | 0.000 |
| 05            | 0.980  | -0.893 | 0.000 |
| 06            | -0.652 | 0.594  | 0.000 |
| 07            | -0.209 | 0.464  | 0.000 |
| 08            | 0.241  | -0.229 | 0.000 |
| 09            | 0.560  | -0.157 | 0.000 |
| 10            | -0.490 | 0.197  | 0.000 |
| 11            | 0.644  | -0.560 | 0.000 |
| 12            | -0.763 | 0.884  | 0.000 |

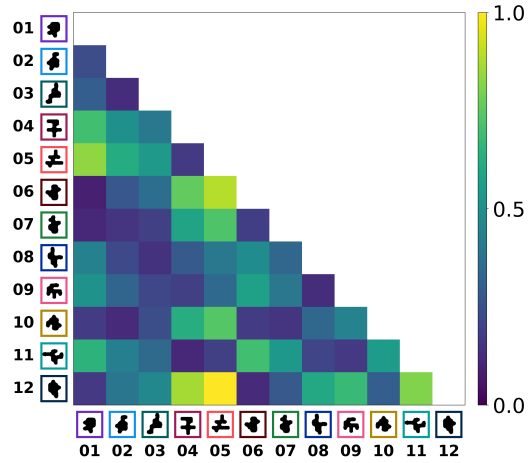
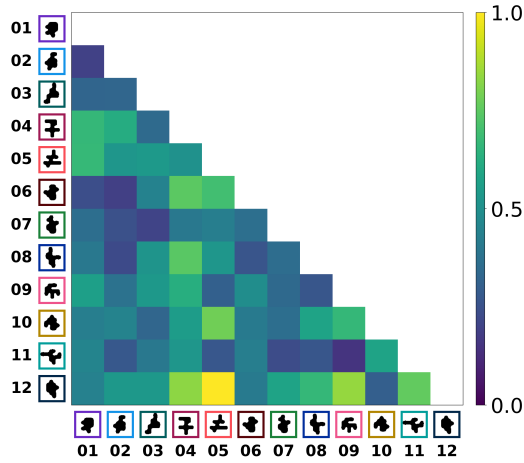
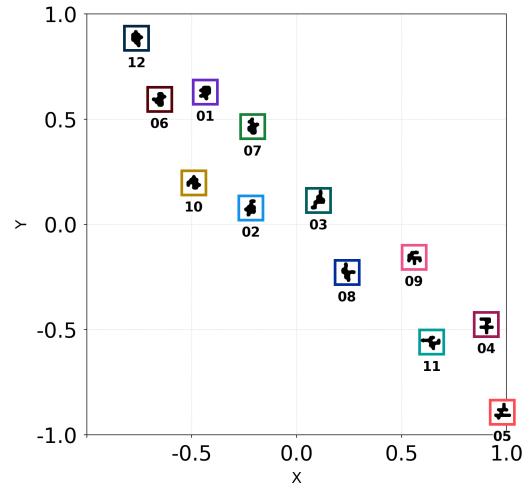
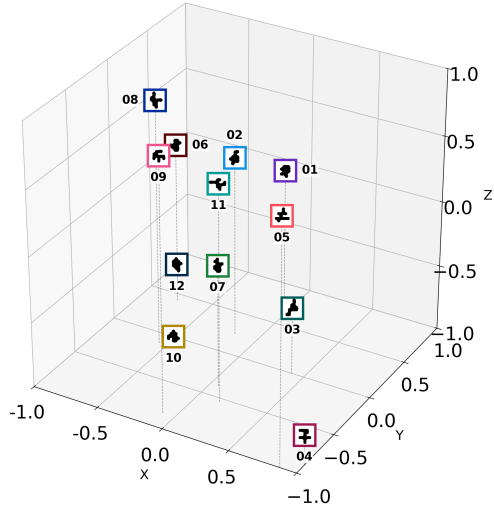
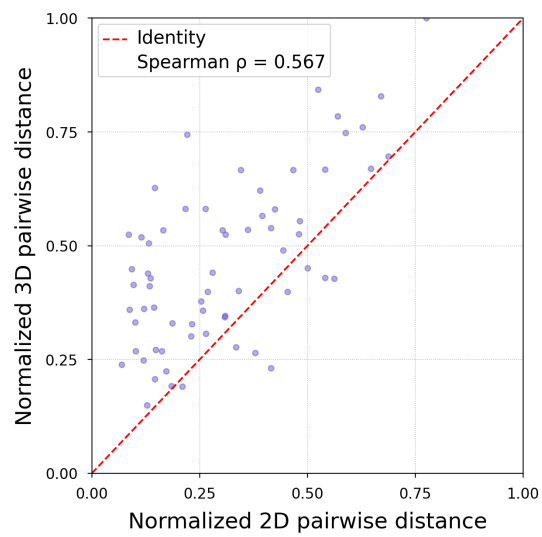
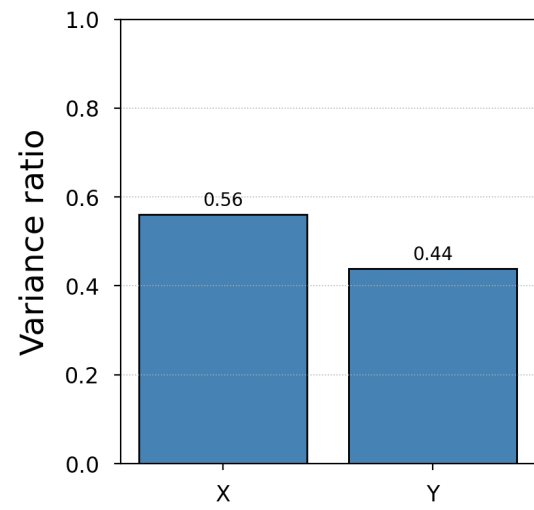
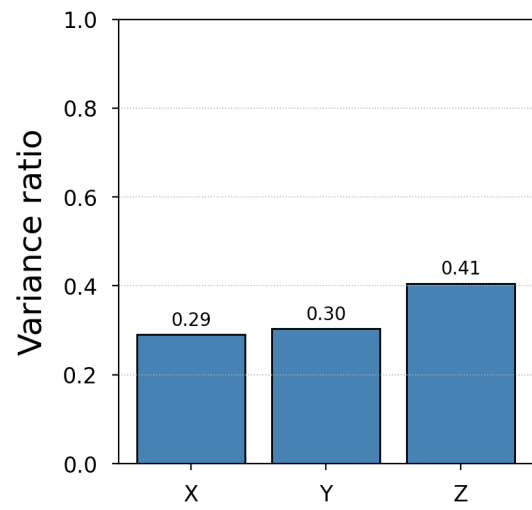
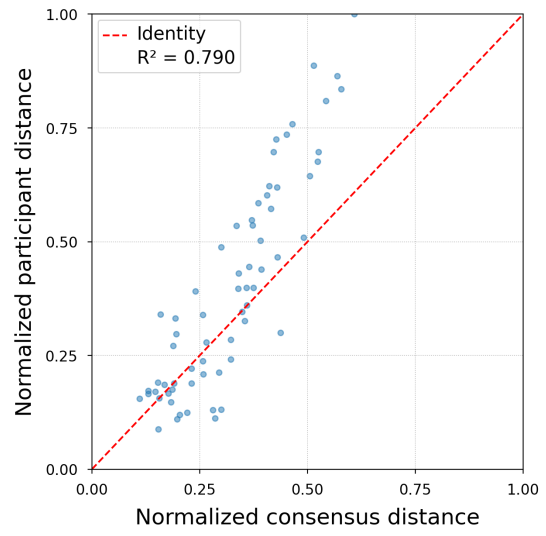
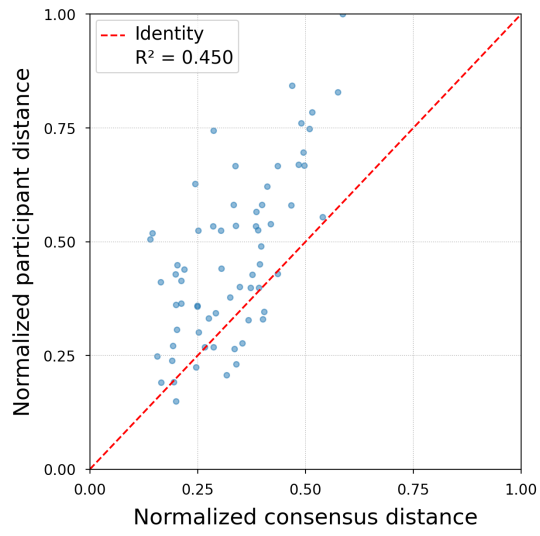


Table 8.: Participant 5: coordinate tables, arrangements, and RDMs.



## Participant 6

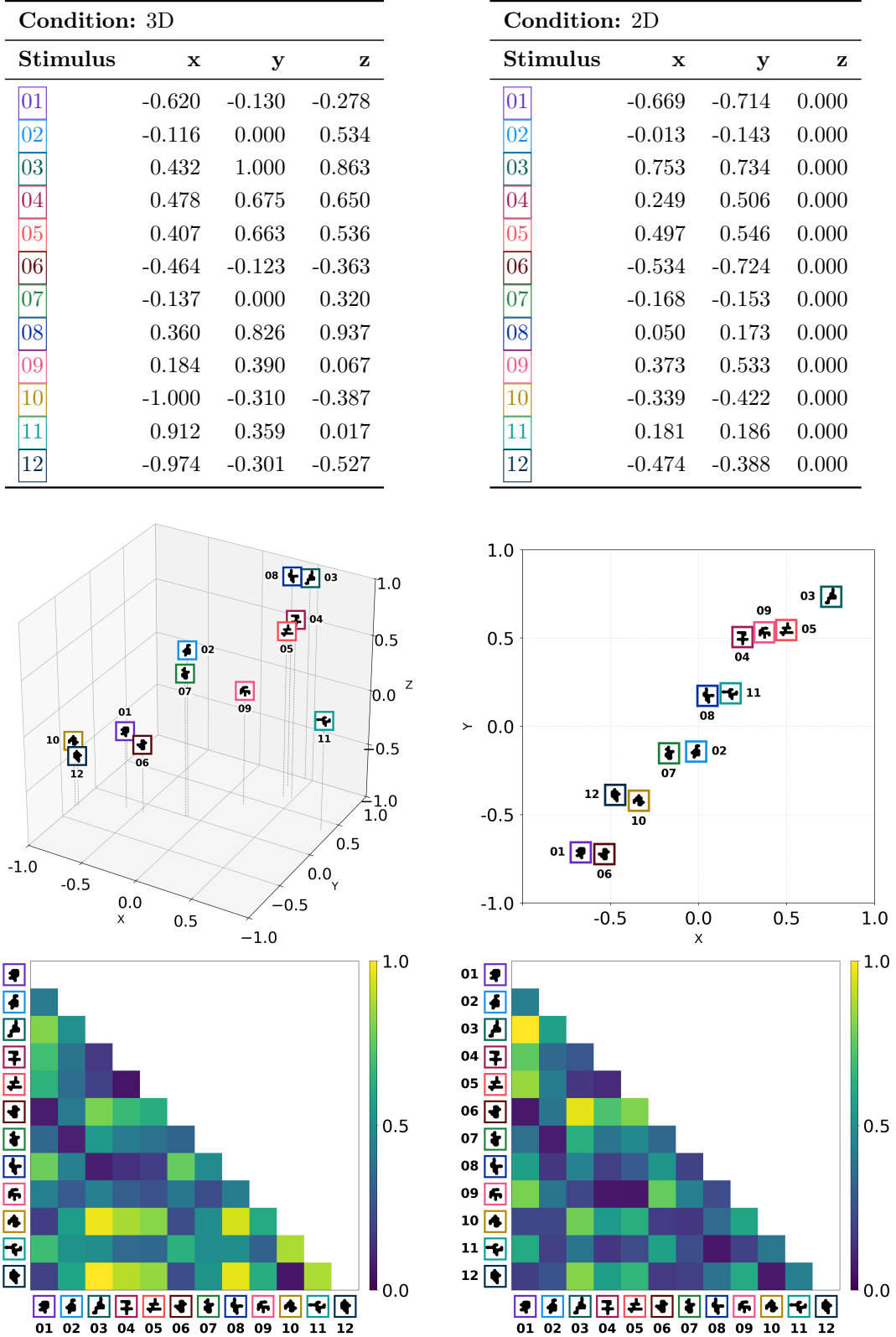
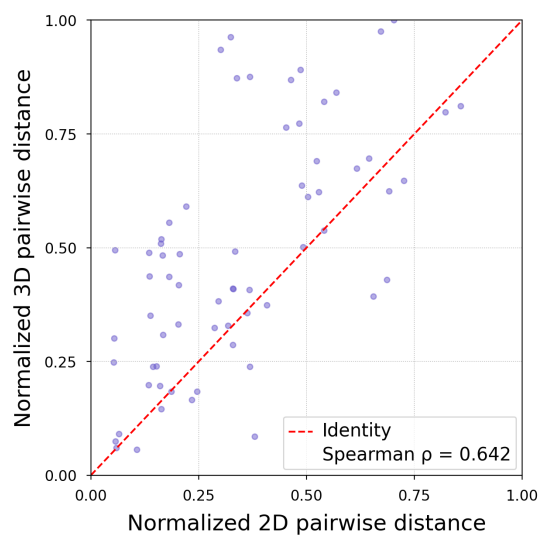
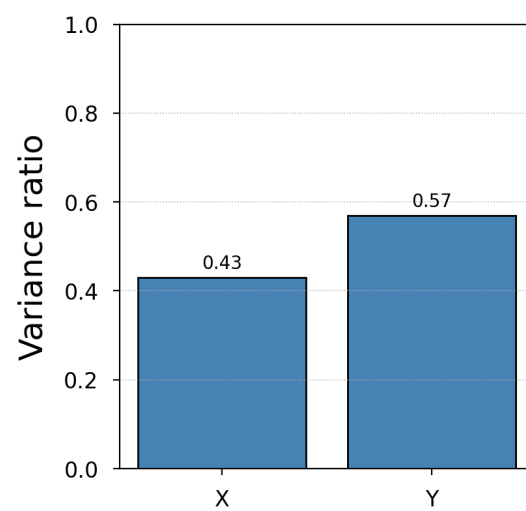
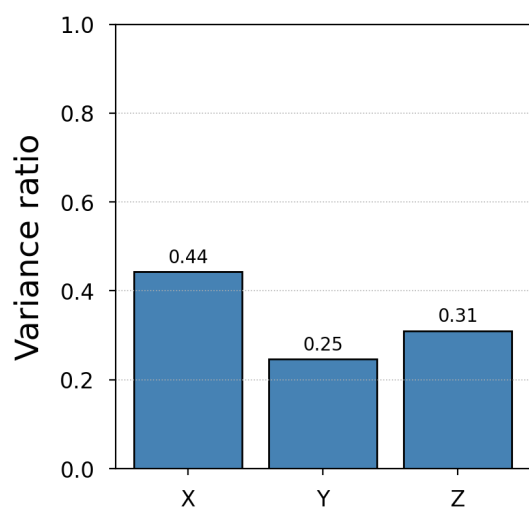
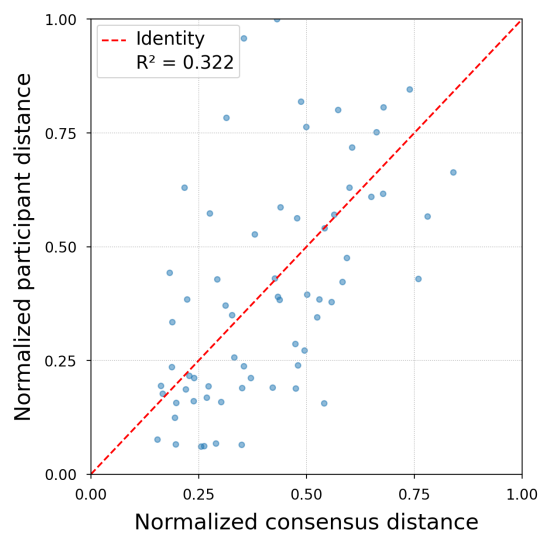
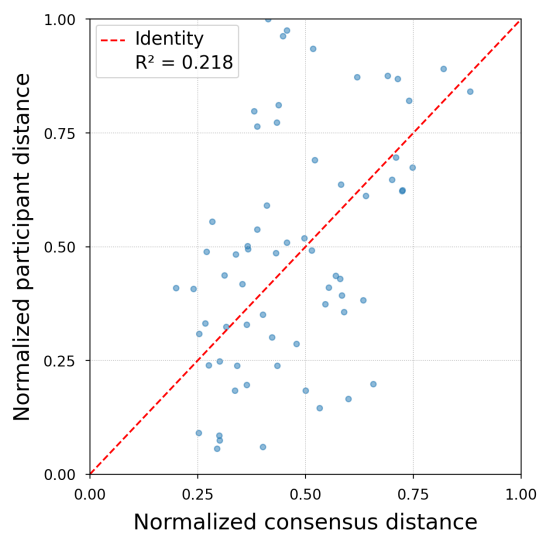


Table 9.: Participant 6: coordinate tables, arrangements, and RDMs.



## Participant 7

| Condition: 3D |        |        |        |
|---------------|--------|--------|--------|
| Stimulus      | x      | y      | z      |
| 01            | 0.526  | -0.180 | -0.959 |
| 02            | 0.739  | -0.360 | -0.667 |
| 03            | -0.256 | -0.060 | 0.015  |
| 04            | 0.285  | 0.420  | 1.000  |
| 05            | 0.979  | 0.780  | 0.767  |
| 06            | 0.065  | -0.420 | -0.675 |
| 07            | 0.197  | -0.420 | -0.243 |
| 08            | -0.025 | 0.000  | -0.005 |
| 09            | 0.614  | 0.780  | 0.970  |
| 10            | 0.422  | 0.000  | -0.873 |
| 11            | 0.838  | 0.480  | 0.751  |
| 12            | -0.016 | -0.600 | -0.529 |

| Condition: 2D |        |        |       |
|---------------|--------|--------|-------|
| Stimulus      | x      | y      | z     |
| 01            | 0.097  | 0.119  | 0.000 |
| 02            | -0.114 | 0.039  | 0.000 |
| 03            | 0.262  | 0.042  | 0.000 |
| 04            | 0.645  | 0.123  | 0.000 |
| 05            | 0.867  | 0.294  | 0.000 |
| 06            | -0.118 | -0.344 | 0.000 |
| 07            | -0.205 | -0.082 | 0.000 |
| 08            | 0.245  | -0.200 | 0.000 |
| 09            | 0.437  | -0.103 | 0.000 |
| 10            | 0.044  | -0.129 | 0.000 |
| 11            | 0.675  | -0.029 | 0.000 |
| 12            | -0.444 | 0.082  | 0.000 |

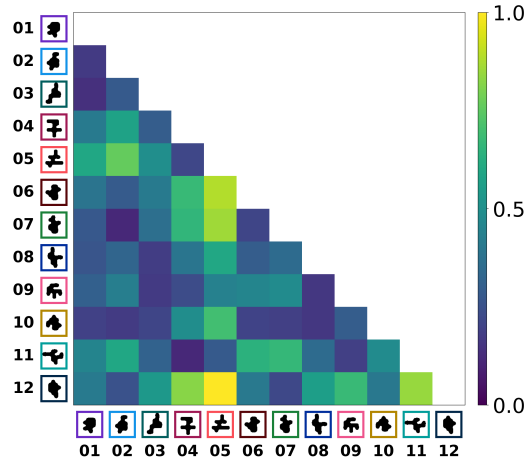
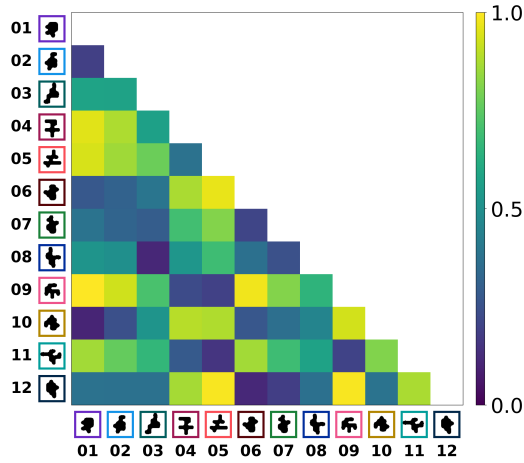
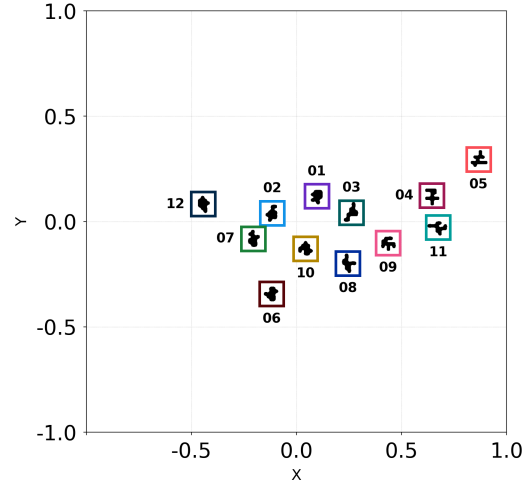
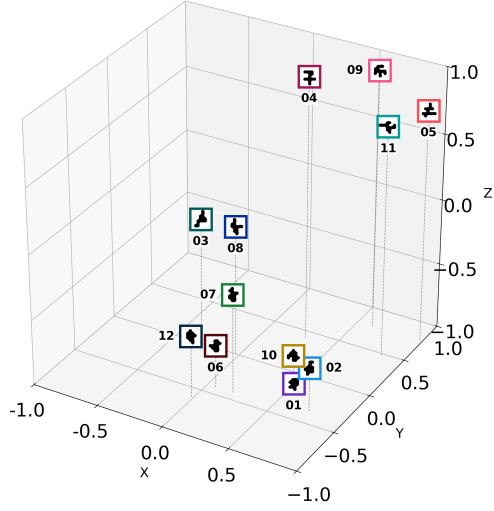
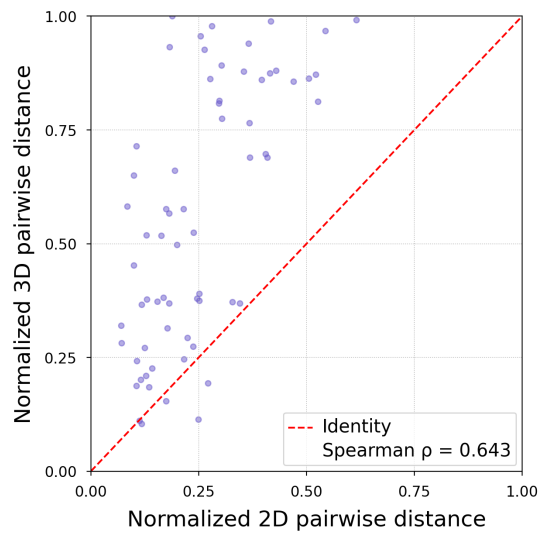
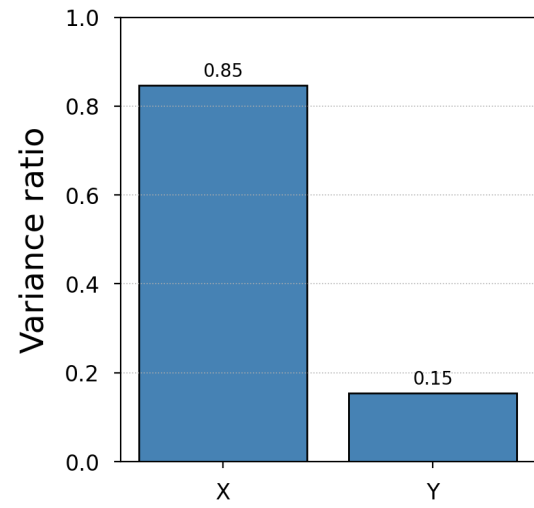
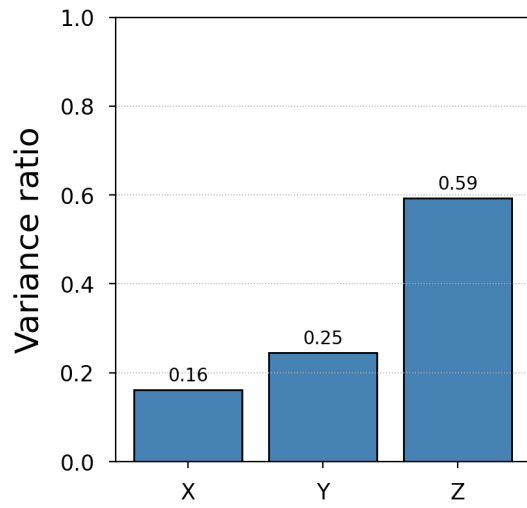
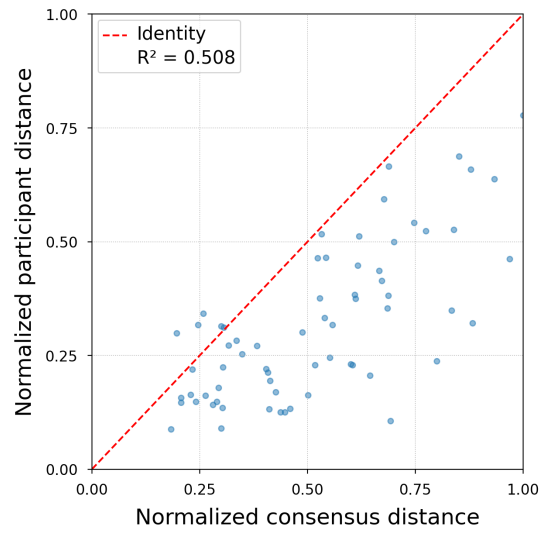
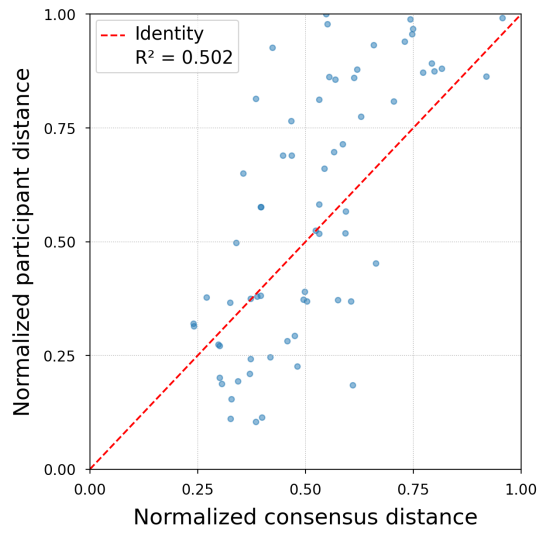


Table 10.: Participant 7: coordinate tables, arrangements, and RDMs.





## D. Supplementary Similarity Diagnostics

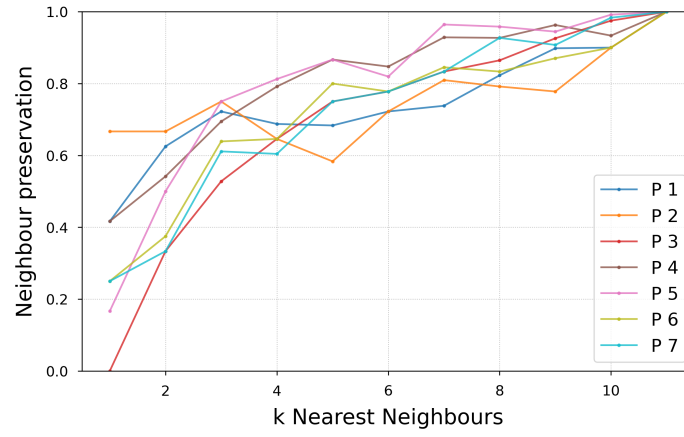


Figure 16.: Individual kNN preservation diagnostics in the 2D condition.

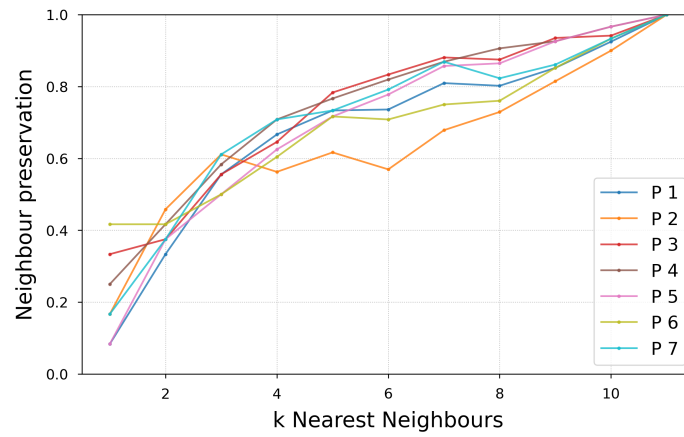


Figure 17.: Individual kNN preservation diagnostics in the 3D condition.

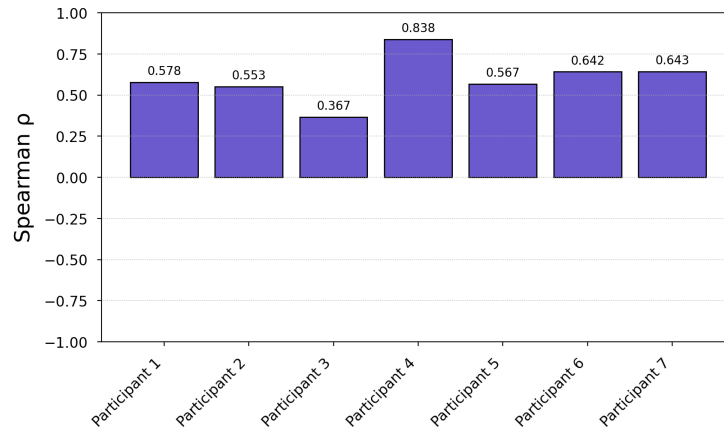


Figure 18.: Spearman rank correlations between 2D and 3D RDMs across participants.

## E. Setup Photograph

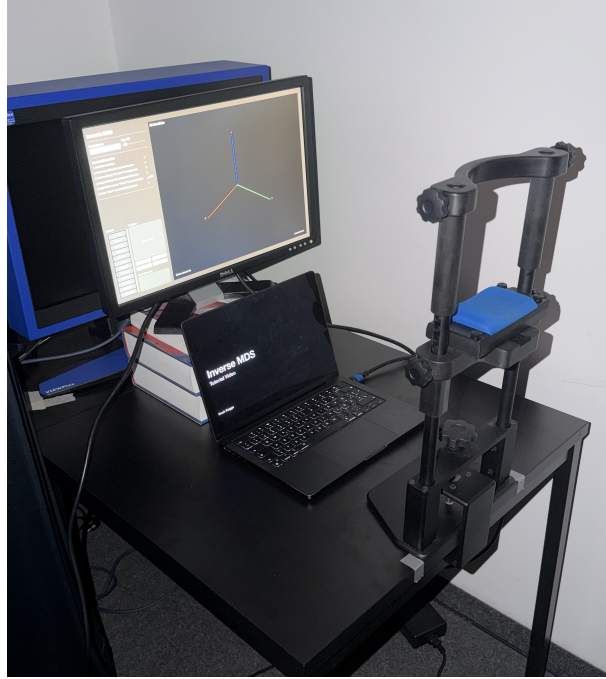


Figure 19.: Headrest and experimental setup.

## F. Visualization Colors

| Stimulus | Color                                                                               | Hex     |
|----------|-------------------------------------------------------------------------------------|---------|
| 1        |  | #6929C4 |
| 2        |  | #1192E8 |
| 3        |  | #005D5D |
| 4        |  | #9F1853 |
| 5        |  | #FA4D56 |
| 6        |  | #570408 |
| 7        |  | #198038 |
| 8        |  | #002D9C |
| 9        |  | #EE538B |
| 10       |  | #B28600 |
| 11       |  | #009D9A |
| 12       |  | #012749 |

Table 11.: Color scheme used for stimulus identification in visualizations.

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# AI Tools

GitHub Copilot (GitHub/Microsoft) and ChatGPT (OpenAI) were used during the preparation of this thesis. GitHub Copilot was mainly used to support programming work, especially during prototyping of the experimental interface. ChatGPT (Codex 5.5) was used to help with spell checking and further language support. All final decisions about the content, wording, analysis, and interpretation were made by me.