# Attentional spatial bias in two image tasks

### Acquisition and analysis of eye-tracking data

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### **Table of contents**

Lis	st o	f Fi	gure	s	IV
Lis	st o	f Ta	bles		IV
1.	lı	ntro	duc	ion	. 1
	Bad	ckg	roun	d	. 2
	Мо	tiva	tion	and research question	. 3
	1.1		Нур	otheses and dependent measures	. 3
2.	Е	Ехр	erim	ental methods	. 4
	2.1		Part	icipants	. 5
	2.2		Mat	erials / stimuli	. 5
	2.3		Stud	dy design	. 6
	2.4		Ехр	eriment (implementation)	. 7
3.	A	\nal	lysis	methods	. 9
;	3.1		Qua	lity control	. 9
	3	3.1.	1	Count of log messages	. 9
	3	3.1.2	2	Amount of triangles	10
,	3.2		Pre	processing	10
	3	3.2.	1	Create subject file pool	11
	3	3.2.2	2	Add additional columns	11
	3	3.2.3	3	Data cleaning	11
;	3.3		Ana	lysis Pipeline	12
	3	3.3.	1	Preparatory steps	12
	3	3.3.2	2	Trial names from <i>df_subject</i>	13
	3	3.3.3	3	Fixation detection	13
	3	3.3.4	1	Plotting Distributions	17
4.	F	Res	ults .		20
5.		Disc	ussi	on	23
;	5.1		How	do findings relate to literature?	25

5.2	Limitations	25
5.3	Challenges during the project	25
5.4	Outlook / improvements / lessons learned	26
6. Coi	ntribution table	27
7. App	pendix	28
7.1	Link to the Git Repository	28
Referen	ces	29
Declara	tion of Authorship	30

## List of Figures

Figure 1: Example images of different categories
Figure 2: OpenSesame experiment sequence
Figure 3: Bar chart showing number of log messages for each of the subjects
Figure 4: Bar chart showing real vs counted number of triangles for each subject 10
Figure 5: Major steps of the analysis pipeline used for each condition separately 12
Figure 6: Steps in the function firstFixationPoints(subject_number, df_subject, trials
dominant_eye)1
Figure 7: Data of one single trial, with the detected fixations marked in the data 10
Figure 8: Fixation distribution for the condition BASELINE
Figure 9: Fixation distribution for the condition SIZE level BIG on the left, and level
SMALL on the right. One plot for the condition applied to the right and one for the
condition on the left
Figure 10: Percentage of the first fixation on the right for the dominant eye for the left
and right image manipulated. Shown for each condition
Figure 11: Percentage of the first fixation on both images per subject for all the
conditions. Per each subject the dominant eye is given next to the subject number 19
Figure 12: First fixation asymmetrical and symmetrical fixation condition
Figure 13: First fixation size big condition and size small condition
Figure 14: First fixation contrary color and dominant color condition 2
List of Tables
Table 1: Different conditions at different levels for stimuli
Table 2: Examples of the image comparison canvas
Table 3: Percentage of first right fixations over all conditions, levels and altered image
Table 4: Percentual right first fixation per dominant eye
Table 5: Contribution table

#### 1. Introduction

Human visual exploration is not spatially neutral. A robust and well-documented phenomenon is the leftward bias in the direction of the first saccade after a central fixation, also referred to as pseudoneglect. This bias manifests as a disproportionate tendency to direct the first fixation toward the left visual hemifield, even in the absence of asymmetries in stimulus content or explicit task demands. This effect is explained by the dominance of the right hemisphere in spatial attention, which leads to more attentional resources being directed to the left visual field (Ossandón et al., 2014).

Ossandón et al. (2014) demonstrated that in right-handed participants, up to 70% of first fixations during free exploration of centrally presented images were directed to the left side within the first 300 ms after stimulus onset, regardless of image category. This early bias was followed by a smaller rightward bias later in viewing, suggesting a temporally structured pattern of spatial attention. The effect was independent of low-level image characteristics such as spatial frequency content, indicating that it reflects attentional, rather than purely sensory, asymmetries.

Consistent results were reported by Hernández-García et al. (2020), who investigated global visual salience in paired-image displays. Across thousands of trials, participants exhibited a systematic initial preference for the image on the left, with approximately 63% of first fixations landing there during free viewing. This leftward tendency persisted even when accounting for task demands and stimulus familiarity, suggesting that it is a stable spatial bias largely unaffected by top-down modulation.

Evidence that the leftward bias also extends to socially relevant content comes from Calbi et al. (2021), who investigated eye movements while participants judged the emotional intensity of static bodily postures. They found that first fixations occurred significantly earlier when directed to the left side, with an average temporal advantage of 162 ms compared to right-sided fixations. This effect was observed across emotional categories and was interpreted as a manifestation of the same left-gaze bias documented in face and scene perception. The authors noted that such a bias may have adaptive relevance, for instance by facilitating the monitoring of the space where another person's dominant hand typically acts.

#### **Background**

Beyond the side preferences in attention, the structure of a stimulus can also guide where people look first. One important feature is symmetry. Eye-tracking studies show that people often direct their first fixation toward the center-of-gravity or symmetry axis of a shape (Kootstra et al., 2011; Lacoste-Badie et al., 2020), and even infants look more efficiently at symmetrical patterns than at asymmetrical ones (Bornstein et al., 2023). For example, when viewing simple geometric figures (like a square or triangle), the very first fixation tends to land near the shape's symmetric center (Lacoste-Badie et al., 2020). Likewise, in more complex images, areas of high mirror-symmetry attract a disproportionately large share of early fixations (Kootstra et al., 2011). This rapid orienting toward symmetry likely reflects the visual system's ability to detect regular, balanced patterns with minimal effort (even infants show fewer gaze shifts for symmetrical patterns) (Bornstein et al., 2023).

Another well-established bottom-up factor in gaze orientation is the size or scale of the stimuli. A large body of eye-tracking research shows larger objects tend to draw eyes sooner and more frequently than smaller objects. In visual search and free-viewing paradigms, increasing an item's size leads to shorter time-to-first-fixation (i.e. observers fixate the large item faster) and a higher probability that it will be the first thing noticed. In fact, the influence of size on attention can be quite robust (Peschel & Orquin, 2013). Lohse (1997) demonstrated that enlarging a stimulus has a stronger influence on gaze allocation than adding color, indicating that size produced a more robust gaze-attraction effect than brightness or color contrast.

Nevertheless, visual attention is also highly sensitive to color contrast. Research on saliency and attentional capture shows that an object with a unique or high-contrast color will automatically attract gaze, even before conscious processes come into play. For instance, in visual search experiments an irrelevant but vividly colored element often "steals" the first eye movement, demonstrating the involuntary pull of salient color differences (Kootstra et al., 2011). More generally, stimuli that strongly stand out colorwise from their background such as a red item against a green background have been found to receive earlier and more frequent fixations than color-congruent or camouflaged stimuli (Peschel & Orquin, 2013). High color contrast effectively increases an item's salience on the retinotopic saliency map that guides reflexive attention (Kootstra et al., 2011). As summarized in Peschel & Orquin (2013) empirical evidence confirms

that making an object's color pop (e.g. a colored ad amid grayscale content) yields a faster initial look and longer gaze dwell on that item.

#### Motivation and research question

The findings discussed above indicate that initial gaze allocation is shaped not only by hemispheric asymmetries, such as the leftward bias, but also by the structural properties of stimuli, including symmetry, size, and color contrast. However, it remains unclear how these factors interact: do certain visual features reinforce the left bias, attenuate it, or even shift gaze toward the right visual field? Addressing this question is essential for clarifying whether early fixations are primarily driven by intrinsic attentional asymmetries or by bottom-up stimulus salience.

In this experiment, we aim to systematically investigate how variations in shape (symmetric vs. asymmetric), size (large vs. small), and background color (dominant vs. complementary) influence the direction of the first fixation after a central fixation point. The study is designed to test whether these manipulations can alter the strength of the leftward bias or even shift it toward the right or whether the bias remains stable regardless of stimulus properties. Accordingly, the key research question guiding this study is:

Does the manipulation of visual stimulus features, specifically shape, size, and back-ground color, lead to systematic differences in the direction of the first fixation (left vs. right) after a central fixation point?

The aim of the study is to determine whether certain visual characteristics of stimuli cause participants to initially look more frequently to one side (left or right) before making a conscious decision.

#### 1.1 Hypotheses and dependent measures

The background literature reviewed in this report highlights three key stimulus properties that can influence initial gaze allocation: symmetry, size, and color contrast. Symmetry has been shown to attract fixations rapidly and consistently, suggesting that deviations from symmetry may be particularly salient to the visual system (Kootstra et al., 2011; Lacoste-Badie et al., 2020). Size has likewise been demonstrated to exert a strong bottom-up influence, with larger objects capturing attention earlier and more reliably than smaller ones (Peschel & Orquin, 2013; Lohse, 1997). Finally, color

contrast especially when based on complementary hues enhances salience and often determines which stimulus is fixated first (Peschel & Orquin, 2013).

Building on these findings, we formulate the following hypotheses:

#### 1. Shape Hypothesis (H1):

When two stimuli of different shape (symmetric vs. asymmetric) are presented side by side, the initial fixation is more often directed toward the asymmetric shape.

Independent variable: shape (symmetric vs. asymmetric)

Dependent variable: direction of the first eye movement (left/right)

#### 2. Size Hypothesis (H2):

If one stimulus is larger than the other, participants will more frequently direct their first fixation toward the larger stimulus.

Independent variable: size (large vs. small)

Dependent variable: direction of the first eye movement (left/right)

#### 3. Background Hypothesis (H3):

When stimuli are shown against a background color, the side where the stimulus has a complementary background will attract the first fixation more often than the side where the background is dominant.

Independent variable: background color (dominant vs. complementary)

Dependent variable: direction of the first eye movement (left/right)

Across all hypotheses, the primary dependent measure is the direction of the first saccade after a central fixation point (left vs. right). This allows to directly test whether lowlevel stimulus features can modulate or override the robust leftward bias described in previous research.

### 2. Experimental methods

To examine whether these stimulus features can indeed modulate the leftward bias, we designed an experiment with the following setup.

The experiment was conducted in a quiet, low-distraction room under constant lighting conditions to minimize external influences on the measurement as much as possible. Participants were presented with a full HD screen (1920x1080 pixels) at a viewing distance of approximately 50 cm. The participants sat on a fixed chair to ensure a stable

starting position throughout the experiment. Eye movements were recorded with a GazePoint GP3 HD eye-tracker at a sampling rate of 150 Hz.

Before the actual measurement began, the participants received an introduction to the experiment and a detailed explanation of the task. This was followed by calibration of the eye tracker, which was supplemented by recalibration during the experiment if necessary. At least one experiment supervisor was present throughout the entire procedure to monitor the process, resolve technical problems, and answer questions from the participants.

Each session followed a clear sequence: first, there was an introduction, followed by calibration of the eye tracker and then the actual experiment.

#### 2.1 Participants

A total of 20 people, age between 21 and 28, took part in the study, including eleven male and nine female participants. All participants were right-handed. When recording the dominant eye, it was found that 12 people were right-eyed and 8 were left-eyed. All participants came from cultures with a left-to-right reading direction. In terms of visual acuity, the majority of participants had normal or corrected vision. One person wore contact lenses during the experiment, and three others wore glasses. Additionally, two participants reported having a red-green color vision deficiency. Recruitment was carried out on a voluntary basis among the researchers' contacts, with no financial remuneration or other compensation being offered for participation. All participants were informed in advance about the procedure, the basic conditions, and the scope of the experiment and subsequently signed a written consent form. The collection and processing of the data was carried out in strict compliance with anonymity and in accordance with ethical standards.

#### 2.2 Materials / stimuli

Images from three categories were used for the experiment: nature<sup>1</sup>, urban<sup>2</sup>, and indoor<sup>3</sup>. Each category contains 100 images selected from a popular online database. The stimuli consisted of two types: baseline images and manipulated images. While the baseline conditions presented the original images without modification, accounting for 20% of the trials, the manipulation conditions specifically varied individual

<sup>&</sup>lt;sup>1</sup> https://www.kaggle.com/datasets/arnaud58/landscape-pictures?resource=download

<sup>&</sup>lt;sup>2</sup> https://www.kaggle.com/datasets/heonh0/daynight-cityview

<sup>&</sup>lt;sup>3</sup> https://www.kaggle.com/datasets/itsahmad/indoor-scenes-cvpr-2019

characteristics of the images, accounting for 80% of the trials. The stimuli differed in terms of size (normal, small (75% the size of normal) and large (125% the size of normal)), shape (symmetrical and asymmetrical), and background color (dominant color of the image and complementary color of the dominant color), each adapted to the image category. In addition, a small red triangle was randomly placed on the images with a probability of 60%, which the participants had to count.

conditions	levels	within/between
size	small, normal, big	within subjects
shape	symmetrical, asymmetrical	within subjects
background	complementary, dominant color	within subjects

Table 1: Different conditions at different levels for stimuli











Figure 1: Example images of different categories

#### 2.3 Study design

To generate trials and assign them to the participants a python script<sup>4</sup> has been written. The script begins with a configuration phase in which a random seed is set to make the results reproducible. Then the framework conditions of the experiment are defined: there are 20 test subjects, each of whom undergoes 120 trials. There are 100 images available for each of the three categories: nature, urban, and indoor. Of all trials, 20% are to serve as baseline trials, while the remainder are generated through manipulation. The types of manipulation are size, shape and background, with each manipulation occurring in two different forms. To shape pairs, image names such as urban\_001.jpg for example are first generated for each category. Then, all possible image pairs from different categories are formed and randomly mixed. During initialization, the script creates an empty list of trials for each test subject. In addition, it stores

<sup>&</sup>lt;sup>4</sup> https://github.com/MadlenBartsch/EyeTracking Projekt/tree/main/scripts/SetGenerator

which images have already been used and how many baselines and manipulations per type and variant have already been assigned. When assigning the image pairs, each pair is assigned to two different test subjects: one receives the pair in the shape  $img_left = A$ ,  $img_right = B$ , while the other receives it mirrored ( $img_left = B$ ,  $img_right = A$ ). The subjects are cycled through in pairs, i.e., first  $subject_1$  and  $subject_2$ , then  $subject_3$  and  $subject_4$ , and so on. The actual trial creation distinguishes between baseline and manipulation trials. If baselines are still missing, the attributes are set to none, and a random image is selected as the target. The counterbalancing index ( $cb_index$ ) is coded as  $baseline_nature_inter_int$ 

#### 2.4 Experiment (implementation)

The experiment was divided into two phases of the software structure. In the prepare phase, the stimuli were loaded and prepared, whereas in the subsequent run phase, the stimuli were presented, and the eye-tracking data was recorded simultaneously. The division into the "prepare" and "run" phases was carried out due to performance issues.

The sequence of a single trial was always structured in the same way (Figure 2): First, a central fixation point appeared to control the starting position of the gaze. The participant then had 10 seconds to look at it, otherwise it was assumed that the calibration was no longer correct, and recalibration was necessary. However, if the participant looked at the fixation point within 10 seconds, two images were displayed simultaneously on the screen for 4 seconds, each of which had a 60% probability of showing a small red triangle. The participant was given the task of counting the number of triangles. After every 10 trials, the number of triangles counted was queried via an input window. The number entered as well as the number of triangles displayed were then logged.

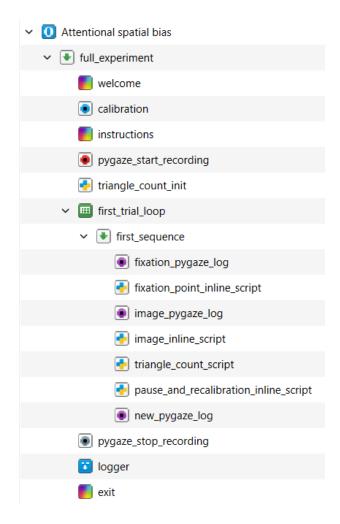


Figure 2: OpenSesame experiment sequence

The planned experiment duration was approximately 20 minutes. However, considering calibration and possible recalibration, the total duration was extended to up to 30 minutes. To prevent visual fatigue for the participants, breaks were taken after trial 40 and 80, if necessary, each followed by recalibration of the eye tracker.

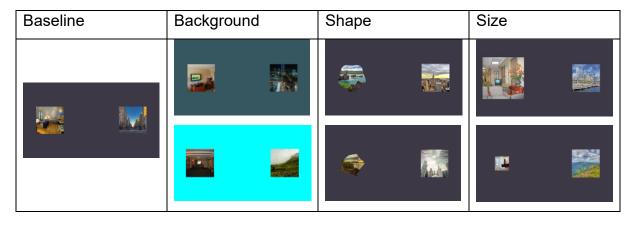


Table 2: Examples of the image comparison canvas

#### 3. Analysis methods

To ensure the data quality and to find out if the conditions can contradict a left bias multiple analysis methods are used. The methods for quality control and the analysis pipeline are implemented in a Jupyter Notebook<sup>5</sup>. The steps of the analysis methods can be outlined as follows: first the data import and preprocessing, separation of trial condition, getting relevant data and fixation, labeling fixations and plotting the fixation distribution. In the following chapters and paragraphs, all these steps and the quality control are described in detail.

#### 3.1 Quality control

The data collected needs to be accurate, usable and reliable before it can be analyzed. Since there are four conditions with two levels each and a lot of trials, it is also important to make sure the experiment is being executed well and all the data needed is in the output files. This can help to detect data loss or a malfunctioning experiment.

#### 3.1.1 Count of log messages

As a first measure the number of log messages is counted for each subject. Three different log messages are counted, the number of fixation logs, the number of trial starts and the trial ends. Figure 3 shows an overview of the log message numbers for each participant.

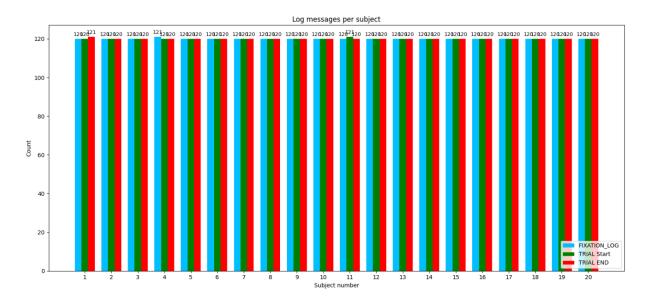


Figure 3: Bar chart showing number of log messages for each of the subjects

9

<sup>&</sup>lt;sup>5</sup> https://github.com/MadlenBartsch/EyeTracking Projekt/tree/main/scripts

#### 3.1.2 Amount of triangles

The task for the participants is to find the triangles in the images. As an evaluation of the triangle visibility the real number of triangles is compared to the counted amount from the participant. The real and counted numbers of the triangles are saved with the trial names in a log message. The amounts need to be extracted and are plotted with the subject number in a grouped bar chart. The difference between real and counted triangles per subject can be seen in the following Figure 4. Since there are participants with color blindness, the triangle count can be decreased. Visual acuity also plays a role here. Depending on how well the participants can see, they may or may not be able to recognize triangles. In addition, the number of triangles counted depends on how quickly the participants can recognize the red triangles. Of course, it can also happen that the triangle is lost in the image.

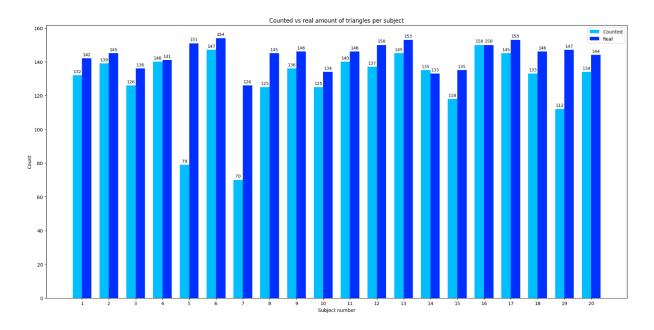


Figure 4: Bar chart showing real vs counted number of triangles for each subject

After the quality control the analysis of the collected data can be carried out.

#### 3.2 Preprocessing

Before the analysis pipeline function can be called, preprocessing steps need to be executed. The main preprocessing function executes all the steps at once which are defined by the three other functions. After calling the main function a data frame of all the individual subject data frames is returned. All the following sub chapters are in the main function. In the first preprocessing sub-step a function is called to create a pool of all the subject files.

#### 3.2.1 Create subject file pool

The function gathers all the data in a data frame which is needed to create an individual subject data frame that has all the relevant columns. The path to the file with the eye tracking data, the subject number and the dominant eye are saved for each subject in one row. This data is hardcoded, and no input is taken by this function. All relevant data is grouped together in a row. This allows the next step to iterate through each row of the data frame. In total there are as many rows as subjects in the experiment. The second major preprocessing step is then performed individually for each row.

#### 3.2.2 Add additional columns

In the second step, columns with subject number and dominant eye are added. This later helps to group fixation points per subject and to check if the dominant eye has any influence on the first fixation. Therefore, the data is read in from the data file which returns a pandas data frame. Next, two new columns are added to the dataframe by  $df['subject'] = subject\_number$  and  $df['dominant\_eye'] = dominant\_eye$ . Since this step is done for each subject data frame the input variables for subject number and dominant eye are given by the row in the function call  $addColumns(row['data\_path'], row['subject\_number'], row['dominant\_eye'])$ . This returns a data frame with all the data collected during the experiment and additional subject information. In the last preprocessing step, the data needs to be cleaned.

#### 3.2.3 Data cleaning

In this function invalid rows are discarded. This is achieved by df = df[df['FPOGV']] == 1]. FPOGV hereby indicates whether a data point is valid or not. This is also done for each row of the subject file pool data frame. So, each subject data which is returned in the second step is handled separately. Here the third function in the main function comes to an end.

At the end of the iteration loop in the main function the individual data frames are added to one big data frame. The separate data frames are arranged in the big data frame in a way it can be iterated and extract one subject data frame at a time. The idea here is to treat each data set individually in the analysis pipeline. The big data frame is then returned and used in the analysis pipeline. After these preprocessing steps the analysis pipeline begins.

#### 3.3 Analysis Pipeline

The analysis pipeline includes preparatory steps, getting the relevant data and fixations and the fixation distribution visualization. The data frame with all the subject datasets and the condition name are the starting point in the pipeline. The analysis pipeline is therefore done for each condition separately. By that it is already easier to compare the effect between the different conditions.

For the analysis pipeline a python function *plotCondition(condition\_name)* is created which takes the condition as a string as an input parameter. An overview of all the steps in the function is shown in Figure 5. In the following paragraph the overview is briefly described.

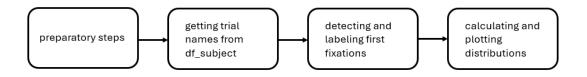


Figure 5: Major steps of the analysis pipeline used for each condition separately

The function uses the data frame returned after the preprocessing. Each subject data frame is then examined individually for fixations by iterating through the rows of the large data set. One row saves one subject data set. Then a set of fixations is created out of the subject data set. At the end, the fixation points of all subjects are combined into one large set. The analysis pipeline thus returns a set of fixations for one condition and plots the distribution. In the following paragraphs the steps in between the start and end point are explained in more detail. The next three steps in the pipeline are inside the loop which iterates over the data frame containing all separate subject data sets. The steps are described in detail in the following sub chapters.

#### 3.3.1 Preparatory steps

In the preparatory steps, a subject dataset is retrieved and assigned to the data frame *df\_subject* via *row['subject\_data']*. In addition, the dominant eye and subject number variables are assigned, which will be needed in the next steps to return the trial names and the fixation set. As mentioned, this makes it easier to compare between subjects or by dominant eye.

#### 3.3.2 Trial names from df subject

Now all preparations have been made and all trial names belonging to the given input condition can be filtered out in the individual subject dataset. At the beginning of each trial, a log message is sent, looking the following e.g.:

TRIAL 2: SIZE\_BIG\_R, LEFT IMAGE: INDOOR\_008.JPG, RIGHT IMAGE: NATURE\_099.JPG

All log messages at the start of the trial are structured similarly as the *SIZE* condition. They differ in trial number, level of condition, whether the condition is applied to the left or right image, and which images are shown. To obtain all relevant trial names for the given input condition, the data is filtered using the following command:

The data frame *trials* then contain all the log messages for trials that belong to the input condition. By that it is easier to find the relevant data of the trials. The data frame *trials* are then given as an input parameter to the function detecting the fixations.

#### 3.3.3 Fixation detection

To detect the fixation the python function *firstFixationPoints(subject\_number, df\_subject, trials, dominant\_eye)* is defined. The function can be divided into different steps shown in Figure 6.

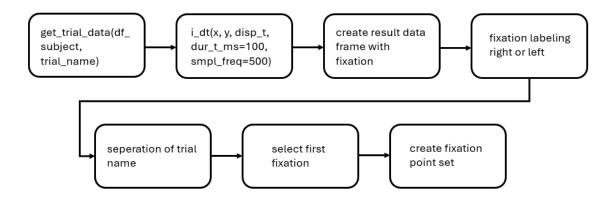


Figure 6: Steps in the function firstFixationPoints(subject\_number, df\_subject, trials, dominant\_eye)

The function only calculates the fixations for one subject since it is still in the first iteration described at the beginning of the pipeline. This step needs the individual subject data frames, the subject number, dominant eye and the set that contains all the trial

names. At the end of the function the fixation points for one subject are returned and then added to a set. The function loops over all the trial names that have been extracted in the previous step.

To get the trial data the subject data, and the trial name is needed. Hence the trial name is extracted from the *trials* set that is input via the function. The variable *trial\_name* is set to *row['USER']* since the trial name and all the information about condition, level and image categories are saved in the log message in the USER column. Because the function loops over all the trial data, the *get\_trial\_data(df\_subject, trial\_name)* function only gets the relevant data in the given data frame *df\_subject* for one trial at a time. At the end of the function *get\_trial\_data*, the fixation point set for one trial is appended to a set which then contains all the fixation points of one subject for one specific condition. The relevant data is marked by two log messages, the first one is the trial name which is the given input, the second one indicates the end of the trial. The data in between these messages is collected while the two images are displayed after the fixation on the centered fixation point. The first log message is shown in section 3.3.1, the second log message is stated as *TRIAL 2: END*. To get the second message, the input trial name needs to be split to get the trial number:

With the two log messages the function determines the starting and the end index of the relevant trial data. At the end of the function all the time values are subtracted by the first time-value *trial\_data['TIME'].iloc[0]* of the trial. The function then returns a data frame containing the trial data that was just described. It includes all the columns that are provided by the eye tracker with the added subject number and the dominant eye.

The columns of the resulting data frame from step one are used by the dispersion-based fixation detection algorithm  $i\_dt(x, y, disp\_t, dur\_t\_ms=100, smpl\_freq=150)$  as an input. This function provides the most important step since the goal is to find out if any condition influences the direction of the first fixation. With the dispersion-based fixation detection the fixations in the eye tracking data can be identified. During a fixation the eye focuses on a place and stops scanning the scene. This results in a group of gaze points in a small area of the scene over a minimum duration. To label data parts as fixation the dispersion of the gaze points is measured. The dispersion-based algorithm slides a window over the data. Then it is checked if the dispersion of the gaze

points is below the dispersion threshold. If the spread of the gaze points is below it is marked as a fixation. The fixation window is extended if the dispersion stays below the threshold.

To use the algorithm the dispersion threshold, the duration threshold, the sample frequency and the eye tracking data needs to be defined. The data frame has the columns BPOGX and BPOGY which are used as input in the fixation detection algorithm. The values indicate the "Best" Point of Gaze X/Y % of screen. BPOGX/BPOGY are the average of the left and right eye for the x- or the y-direction. The function i dt(x, y, y)disp\_t, dur\_t\_ms=100, smpl\_freq=150) takes trial\_data['BPOGX'] as input x and trial\_data['BPOGY']. Trial\_data is the data frame with the relevant data which was returned by the functions described in the first step of Figure 6. The dispersion threshold disp t defines how far the gaze points are allowed to be apart. The number of fixations depend on the dispersion threshold. The duration threshold *dur\_t\_ms* is the minimum amount of time a gaze needs to stay within the allowed dispersion. The start and end indices of the fixation are saved. The fixations in one example trial are visualized in Figure 7. The start indices are marked by green dotted lines, and the end indices are marked by red dotted lines. With the detected fixations a data frame is created, this refers to the third step in Figure 6. With the starting and ending index, the starting time, end time and duration are saved as columns in the newly created data frame. In addition, the values of the fixation points on the discovered indices are added. After that, the fixations are labeled whether the participant focused on the right, left or no image. Therefore, another method is defined, depending on the value of BPOGX the position of the image can be determined on the screen.

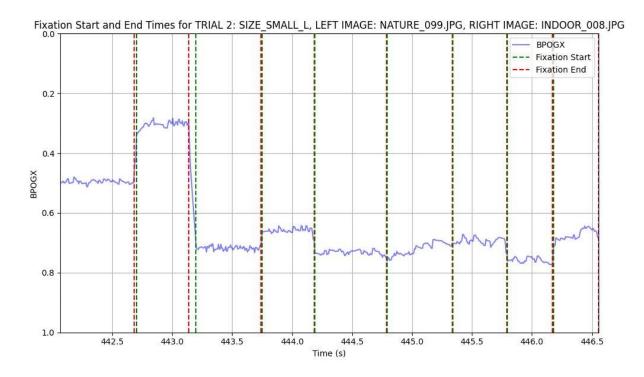


Figure 7: Data of one single trial, with the detected fixations marked in the data

The third and fourth steps result in a data frame that contains participant information, start and end of the fixations, the image label and the trial and condition name. This leads to the fifth step in the function *firstFixationPoints*. To be able to analyze the effect of the condition and their levels, the trials need to be separated by their condition, level and on which image the condition is applied. The log message which was used to separate the trials is also used to extract the level and condition of the trial. Additionally, the image on which the condition is applied is extracted from the log message. Also, the image categories are saved in the final fixation point list. For both images the category is saved with the log message during the experiment.

After the separation of the trial name, the first fixation that has either left or right image as label for each trial is chosen. After all this, the last step in Figure 6 is being carried out. The first fixation is saved in a point list. For each fixation point, the condition name, the level name, the image categories, the subject number, dominant eye and the label is saved. The fixations and their details are saved as follows:

{'trial': 'TRIAL 2: SIZE\_BIG\_R, LEFT IMAGE: INDOOR\_008.JPG, RIGHT IMAGE: NA-TURE\_099.JPG', 'condition': 'SIZE', 'level': 'BIG', 'image': 'R', 'left\_cat': 'INDOOR', 'right\_cat': 'NATURE', 'label': 'right image', 'subject': np.int64(1), 'dominant\_eye': 'left'}

All the lists are then added to a list where all the fixation points of one subject for one condition are stored. At the end of this function a fixation point list for one subject is returned. It is then added to the fixation point lists for all the subjects. This concludes the first loop in the function *plotCondition(condition\_name)*. Now only the last step is missing in the analysis pipeline. The distribution of fixations must be calculated and then plotted.

#### 3.3.4 Plotting Distributions

For the calculating and plotting the python function *plotDistribution(fixation\_points)* is defined. All initial fixation points from all subjects for the given condition are the input for the function. To plot the distributions a distinction must be made between the different levels. For the conditions *SIZE*, *SHAPE* and *BACKGROUND* the procedure is equal because the conditions have two levels. Here a distinction needs to be made, for example for *SIZE* whether the level is *BIG* or the level is *SMALL*. This helps to analyze the results in more detail. In addition, for these three conditions, a distinction must also be made as to whether the level has been applied to the left or right image. For the *BASELINE* condition there is only one level, and nothing has changed in both images. For each condition, the labels need to be counted from the first fixation points, and then the distribution needs to be plotted. As a plot a horizontal bar plot is chosen. Before plotting, the counts need to be converted to percentages of the total amount with *count/total* \* 100. To plot the distribution a horizontal bar plot and two colors indicating left and right are used. The plot for the *BASELINE* condition can be seen in Figure 8.

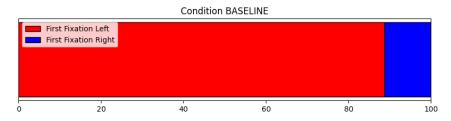


Figure 8: Fixation distribution for the condition BASELINE

The plot for the other conditions has in total four bar plots, one for each level and where it is applied to. This leads to two figures each with two bar plots. Figure 9 shows the bar plots for condition *SIZE* as an example. In the figure the level *BIG* is shown on the left, the level *SMALL* is shown on the right.

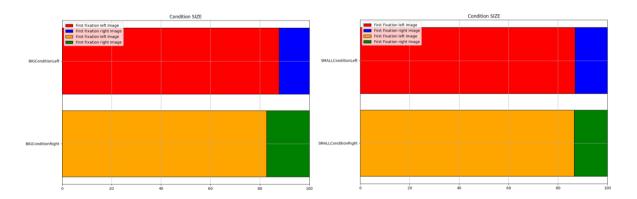


Figure 9: Fixation distribution for the condition SIZE level BIG on the left, and level SMALL on the right. One plot for the condition applied to the right and one for the condition on the left

The plotting of the general distribution is the end of the analysis pipeline. The function  $plotCondition(condition_name)$  used to carry out the analysis pipeline, not only plots the conditions but also returns the fixation sets for the different levels. So, for each condition it returns two different sets except for BASELINE. Here only one set is returned, since this condition has no levels. These fixation sets can be used for further analyzing tasks. From the end of the pipeline, you can then continue to examine the consequences of the conditions in more detail.

Therefore, the percentage of first fixations on the right image per condition for the dominant eyes is plotted. In Figure 10 the percentage is shown for the left and right image altered for each condition for the left and right dominant eye. In Figure 11 the percentages for each subject for all conditions are shown. The dominant eye is plotted with the distribution to make reason of the effect of the dominant eye.

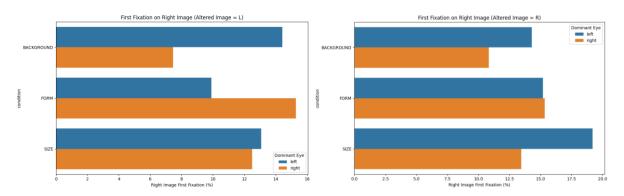


Figure 10: Percentage of the first fixation on the right for the dominant eye for the left and right image manipulated. Shown for each condition

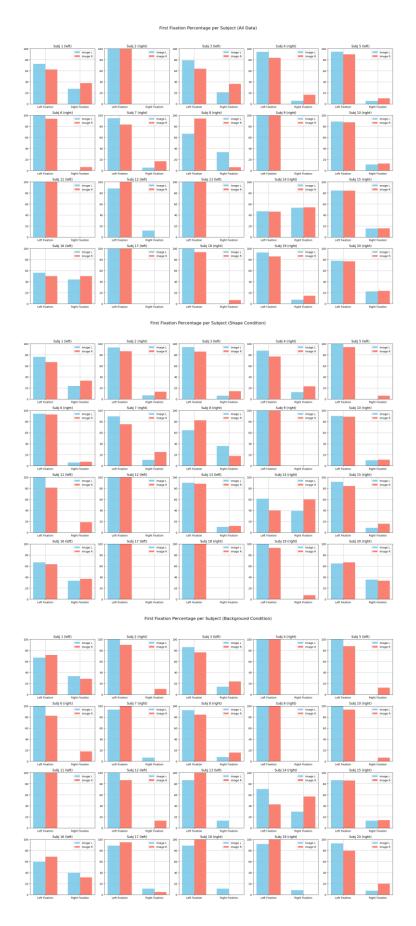


Figure 11: Percentage of the first fixation on both images per subject for all the conditions. Per each subject the dominant eye is given next to the subject number

#### 4. Results

This project aimed to study the effects on the leftward bias when presenting the images under different conditions. In our study we looked at three conditions: size and shape of the images as well as the background color in which the images were presented. As a comparison baseline, we presented the images unaltered. In the baseline condition which can be seen in Figure 8, about 88.71% of first fixations were directed to the left, while only about 11.29% were directed to the right.

For the shape condition either the left or the right image was manipulated by making the image symmetrical or asymmetrical. Capturing the first fixations, we get the results that can be seen in Figure 12. In this figure and in all following figures the red and yellow portions represent the percentage of the first fixation over all trials on the left image, the green and blue portion on the right image. As a result, an asymmetrical shape of the right image achieved 15.33% first right fixation whereas a first right fixation of only 12.5% was achieved when the left image was altered to be asymmetrical. The symmetrical manipulations achieved 14.17% first right fixations when the left image was altered into a symmetrical shape and 15.24% when the left image was altered into a symmetrical shape.

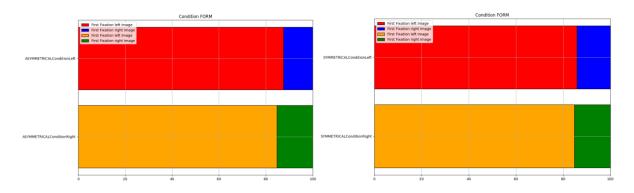


Figure 12: First fixation asymmetrical and symmetrical fixation condition

Similarly, for the size condition, the size of one of the images was altered to either small or big which corresponds to 75% of the normal size and 125% of the normal size. The results of the first fixation can be seen in Figure 13. When the right image was enlarged, the highest percentage of first right fixations was observed with 17.36%. In contrast, when the left image was enlarged, the percentage dropped to 12.24%, the lowest level. For the smaller condition, when the right image was reduced in size, the first right fixation was 13.49%, whereas reducing the left image resulted in 13.17% first right fixations.

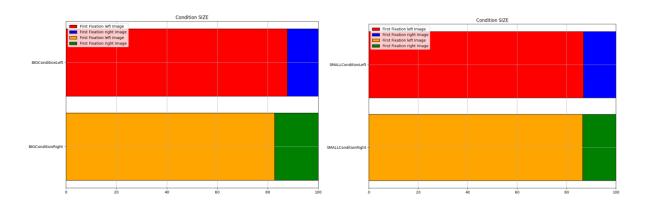


Figure 13: First fixation size big condition and size small condition

Lastly, for the background condition the color of the background was manipulated to either be the dominant or the complementary color of one of the images. Here the first fixation distribution can be seen in Figure 14. The gathered data indicates no significant alteration compared to the baseline. When the background color was changed to the complementary color of the right image, a right fixation of 10.07% was achieved, while altering the left image to have a complementary background resulted in 13.72%. For the dominant color condition, the right first fixation was recorded at 10.78% when the right image was altered and 10.32% when the left image was altered. All values are close (<7%) to the baseline right first fixation of 11.29%.

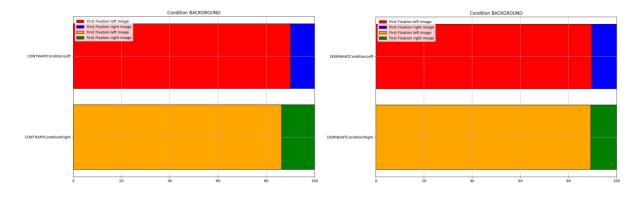


Figure 14: First fixation contrary color and dominant color condition

The results described above are also summarized and presented in Table 3 where the percentage of right first fixations are represented for each condition and further split on which image was altered, right or left. Looking at the bar plots and the table it is noticeable that the background condition has the least influence on the first fixation in comparison to the baseline.

Condition	Level	Altered Image	First Right Fixa-		
Condition	Level	Allered illiage	tion (%)		
Form	Asymmetrical	R	15.33		
		L	12.5		
	Symmetrical	R	15.24		
		L	14.17		
Size	Big	R	17.36		
		L	12.24		
	Small	R	13.49		
		L	13.17		
Background	Dominant	R	10.78		
		L	10.32		
	Contrary	R	10.07		
		L	13.72		
Baseline			11.29		

Table 3: Percentage of first right fixations over all conditions, levels and altered image

Further analysis includes the dominant eye of the participants. A plot of the first fixation per subject was made and can be seen in Figure 11. Additionally, Table 4 and Figure 10 show the percentual right first fixation of the 8 participants with a left dominant eye and 12 participants with a right dominant eye. For the background condition participant with a dominant left eye are more likely to fixate on the right image than right-eye dominants. The shape condition caused difference when the left image was manipulated. Less participants with a dominant left eye fixated first on the right image. For the size condition a similar behavior can be seen across the altered left image. When the altered image is the right image more left-eye dominants look at the right image first. Table 4 and Figure 10 show that left-eye dominants are more drawn to the right image when its altered compared to the right-eye dominants. But Figure 11 shows that the left bias is the main effect across all subjects. In that left bias smaller effects in connection with the dominant eye and altered image can be seen.

Dominant Eye	Altered Image	Condition	First Right Fixation (%)
Left	L	Background	14.42
		Shape	9.9
		Size	13.07
	R	Background	14.29
		Shape	15.2
		Size	19.19
Right	L	Background	7.45
		Shape	15.29
		Size	12.5
	R	Background	10.82
		Shape	15.34
		Size	13.45

Table 4: Percentual right first fixation per dominant eye

#### 5. Discussion

The goal of this project was to investigate whether the initial gaze is influenced not only by hemispheric asymmetries, such as the left bias, but also by specific stimulus properties, namely shape (symmetric vs. asymmetric), size (large vs. small), and background color (dominant vs. complementary). For this we used our three hypotheses:

- H1: When two stimuli of different shape (symmetric vs. asymmetric) are presented side by side, the initial fixation is more often directed toward the asymmetric shape.
- H2: If one stimulus is larger than the other, participants will more frequently direct their first fixation toward the larger stimulus.
- H3: When stimuli are shown against a background color, the side with a complementary background will attract the first fixation more often than the side with a dominant background.

To test these hypotheses, we recorded the eye movements of 20 participants while presenting them with pairs of images, one on the left and one on the right, each

corresponding to one of the three conditions. From the recorded data, we extracted the position of the first fixation, either left or right.

For the first hypothesis, our data suggests a slight increase in the first right fixations when the asymmetric shape was presented on the right side. However, since this effect was small, the hypothesis cannot be fully supported. When a symmetric shape was shown, either on the left or right, the amount of first right fixations increased compared to the baseline. Interestingly, it did not seem to matter on which side the symmetric shape appeared. This likely indicates that more data or a differently designed experiment would be necessary to draw clearer conclusions.

The second hypothesis also cannot be fully supported. While we observed more first right fixations when the larger stimulus was presented on the right side, there was no significant increase in first right fixations when the smaller stimulus was on the left. Based on the relative size difference, we would also have expected more right fixations in this case. Similarly, when the smaller stimulus was presented on the right, there was no corresponding decrease in right fixations, contrary to our expectations. These results suggest that the size of the images does influence the direction of the first fixation, but further research is needed.

Overall, while shape and size appear to have some effect on the direction of first fixations, the effect is relatively small, as a strong left bias persisted despite these manipulations.

In contrast, the third hypothesis was not supported. Changing the background color did not lead to an increase in right-sided fixations. Whether the background was dominant or complementary made no measurable difference. This suggests that background color has no effect on the left bias.

To answer our research question, our results indicate that modifications of shape and size can lead to systematic differences in the direction of the first fixation after a central fixation point, whereas background color shows no effect. However, as previously stated, further research is needed to make more precise statements about how shape and size influence the bias.

#### 5.1 How do findings relate to literature?

We found that approximately 86% of first fixations were directed to the left side. This result is consistent with previous studies, such as Ossandón et al. (2014), who also reported a leftward bias in first fixations, and Hernández-García et al. (2020), who observed that 63% of first fixations landed on the left image.

Our findings on the influence of size are consistent with previous research. Like Lohse et al. (1997), we observed that participants tended to fixate more often on larger images. However, in contrast to Lohse et al. (1997), who reported that participants were more likely to look at colored advertisements compared to black-and-white ones, we did not find an effect of background color on fixation behavior. However, since they considered the color of the images, while we considered the background color no direct comparison can be drawn.

#### 5.2 Limitations

One limitation of this project is that all participants were between 21 and 28 years old. The lack of age diversity may have influenced the results, as different age groups could show distinct patterns in their first fixation. In addition, the sample size of 20 participants is relatively small, which limits the generalizability of the findings. Another limitation of the project is that, despite the use of counterbalancing, variations in the image content may still have influenced the participants' initial fixation choices. Finally, all participants came from cultures with left-to-right reading and were right-handed, which may have shaped their gaze behavior and introduced bias.

#### 5.3 Challenges during the project

The project encountered several challenges. One challenge was performance issues during the experiment. Displaying the images took a considerable amount of time, resulting in random pauses during the experiment. We addressed this by preloading the images in the preparation phase of the script, which drastically improved the display speed. Another challenge was the detection of the first fixation, which required determining suitable parameters for the dispersion-based algorithm. We approached this by estimating the parameters from the collected data. The duration of the experiment also posed a difficulty, as participants occasionally experienced eye strain and fatigue. To mitigate this, we included breaks that participants could take as needed. Furthermore, some participants encountered problems with the eye tracker, requiring

frequent recalibrations, which in turn prolonged the experiment. Recruitment of participants presented another challenge, as it was difficult to find enough individuals willing to come to the eye tracking lab to take part. Finally, we initially struggled to gather enough images for our dataset. This challenge was resolved by making use of a large online dataset.

#### 5.4 Outlook / improvements / lessons learned

A possible outlook for future research is to investigate the influence of the dominant hand or to focus more on the influence of the dominant eye on the first fixation. The effect of the primary reading direction, such as left-to-right or right-to-left, on first fixations could be as well investigated. Moreover, future studies could consider a wider variety of stimuli to examine how different properties affect the first fixation.

Several improvements to the experiment could also be considered. For instance, the area of the images after applying symmetric or asymmetric shapes should be considered, as these manipulations reduce image size and thus introduce size differences. Additionally, a different search task could be used, since the current task caused difficulties for participants with color vision deficiencies and may have introduced bias in the first fixation. It would also be beneficial to consider the colors of both images when modifying the background color, as similar colors in both images could skew results regarding the influence of background color on the left bias. Finally, including an example trial at the beginning of the experiment would help participants understand what to expect and potentially improve data quality.

The main lessons learned from this project include the importance of setting up the eye tracker correctly to ensure good data quality. We also learned to allow enough time between participants, so they do not have to wait if problems occur, and how to handle situations when the experiment does not go as planned, such as when the eye tracker needs frequent recalibration. Additionally, we recognized the importance of ethical considerations when working with participants, including obtaining consent, explaining the experiment clearly, and following ethical guidelines. Finally, we gained experience in working with eye-tracking data, such as detecting fixations and removing invalid data.

### 6. Contribution table

Task	Alexander	Fran-	Jan-	Julian	Sven	Madlen
		ziska	Luca			
Background Literature		х				
Experiment Design	Х	х	х	Х	Х	х
Stimulus Design		х	Х	Х		Х
Piloting		х	Х	Х		0
Data Recording	Х	х	0	0		0
Non-Final-Talk (who talks)	Х	х	Х	Х	Х	х
Non-Final-Talk (who prepares)	0	0	0	0		х
Final-Talk (who talks)	Х	х	Х	Х	Х	х
Final-Talk (who prepares)	х	х	Х	Х	Х	Х
Subject set generator script			Х			
Data Analysis Script						х
Quality Control Script	Х					х
Report Introduction		х				
Report Experimental Methods			Х	Х		
Report Analysis Methods						х
Report Results					Х	0
Report Discussion	Х					
Report Formatting		х				
Report Lecturing	0	х	Х	Х	0	Х
Report Revise/Edit/Rework		Х				х

Legend: x = main, o = supporter

Table 5: Contribution table

## 7. Appendix

## 7.1 Link to the Git Repository

The project experiment source code is available at:

https://github.com/MadlenBartsch/EyeTracking\_Projekt#

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#### **Declaration of Authorship**

Hiermit versichere ich,

- dass die Arbeit, bzw. bei einer Gruppenarbeit mein entsprechend gekennzeichneter Teil, selbstständig verfasst wurde,
- dass keine anderen als die angegebenen Quellen benutzt und alle wörtlich oder sinngemäß aus anderen Werken übernommenen Aussagen als solche gekennzeichnet wurden,
- dass keine anderen als die angegebenen Hilfsmittel verwendet wurden,
- dass die eingereichte Arbeit weder vollständig noch in wesentlichen Teilen Gegenstand eines anderen Prüfungsverfahrens war und
- dass die Arbeit weder vollständig noch in Teilen bereits veröffentlicht wurde.

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