# Joint Attention in Human-Robot Interaction, A Case of Eye Gaze-Leading Task

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## Abstract

Central to effective Human-Robot Interaction (HRI) is joint attention, where shared focus on objects facilitates communication and bonding. This study used a gaze-leading paradigm to explore how robot gaze behaviours (following vs. unfollowing) and attributed dispositions (joint vs. disjoint) influence participants' return-to-face saccades, as well as their subjective preference over the robots with different dispositions. In the task, participants were asked to choose one of the objects shown on the screen. In the middle of the objects was a robot face that executed gaze behaviours either to look at their chosen object (following) or look at the other object (unfollowing). It was expected that participants might stimulate a quicker response to reorientate their gaze towards the robot's face when the robot exhibits behaviour that is not expected from its attributed disposition. Results supported the hypothesis that unexpected unfollowing behaviours from joint disposition robots prompt quicker responses to return-to-face-saccades. The subjective preferences for robot likability and anthropomorphism did not vary significantly between the robots with joint and disjoint dispositions. These findings underscore the complexities of human responses to robot behaviours in HRI, suggesting future studies explore additional factors and more naturalistic settings to optimize robot design and interaction.

## Introduction

In the literature on Human-Robot Interaction (HRI), researchers investigate how humans interact with robots, how they perceive robots, and how they correspond to a robot's behaviour (Ahmad et al., 2017; Brondi et al., 2021). A study found that people no longer perceived robots as merely an output for their functions nor as metal objects (Brondi et al., 2021). It is believed that robots have integrated into human daily activities. A state of reciprocity is expected in the interaction with robots (Brondi et al., 2021). People expect to get the same level of responses from robots. For example, on an online platform, people foresee that chatbots can understand their questions and give relevant answers or responses. As a human's kind of mental state is projected onto robots, they are viewed as closer to human beings.

The increasing human-likeness of robots is associated with their perceived ability to understand and predict human states and intentions (Vianello et al., 2021). This perception is crucial in HRI, necessitating the development of robots with advanced interaction skills that closely mimic human mechanisms. These skills significantly influence the robots' ability to engage socially with humans (Vianello et al., 2021). Consequently, the development of humanoid robots focuses not only on enhancing their human-like appearance but also on improving their interaction capabilities, aiming to create a more natural and engaging presence. A crucial mechanism in achieving effective HRI is joint attention. According to Gregory and Jackson (2019), joint attention could be explained through mutual engagement to focus on the same cue. The cue can be an object, a person, or a concept (Gregory & Jackson, 2019). This shared focus creates consensus and facilitates deeper elaboration in subsequent interactions, highlighting its importance in HRI as a mechanism for enhancing engagement.

**Joint Attention**

Joint attention is a fundamental aspect of social interaction and communication, involving two individuals focusing on the same object or event simultaneously while being aware of each other's focus (Gregory & Jackson, 2019). It is a critical component of early development and plays a crucial role in learning, language acquisition, and social bonding (Dalmaso et al., 2020). Some key components clarify how joint attention works. Firstly, joint attention involves the shared focus in the attention of both actors: initiator and responder (Bayliss et al., 2013). An initiator directs the other's attention by giving signals, such as pointing gestures, shifting in eye gaze, or even through verbal cues (Bayliss et al., 2013). Correspondingly, a responder is the one who gets influenced by those signals and responds to follow the signalling direction (Bayliss et al., 2013). The incorporation acts of initiating and responding not only engage the two individuals but also ensure that they both are aware of the shared attention on the same cue. They are concerned about whether each other is attending to the cue. Moreover, joint attention is a dynamic process as both initiator and responder constantly look back and forth between the object and the other person to ensure that the shared attention is maintained (Bayliss et al., 2013).

Eye gaze plays a central role in joint attention, serving as a powerful cue for directing and capturing attention (Emery, 2000). In this context, the co-engage between the two individuals' visual attention helps in information exchange (Morillo-Mendez et al., 2023). The responder of the joint attention would gain social benefits by following the initiator's signal (Bayliss et al., 2013). Thus, by following another's gaze, individuals can infer their intentions, to help in engaging the joint activities more effectively, also helpful in the case of detecting potential threats that were not initially aware of (Bayliss et al., 2013).

Recently, studies have investigated the mechanisms of joint attention through eye gaze responses (Gregory & Jackson, 2019; Willemse et al., 2018; Dalmaso et al., 2020). Two main paradigms used in this context: the gaze-cueing task and the gaze-leading task. In gaze-cueing tasks, researchers examine how individuals respond to others' gaze cues to understand how these mechanisms contribute to joint attention (Dalmaso et al., 2020). In the gaze-cueing task, participants are presented with a central fixation point followed by gaze cues, either an arrow or a human face with averted eyes (Dalmaso et al., 2020). The participant's task is to detect or respond to a target indicated by the gaze cue. This paradigm allows researchers to assess the extent to which participants orient their attention in response to gaze cues. The quicker attention shifts in response to eye gaze cues indicate that it is an automatic response, underscoring the significance of eye gaze in social attention processes (Dalmaso et al., 2020). These findings provide valuable insights into how joint attention is established and maintained through eye gaze.

In contrast, the gaze-leading paradigm explores how individuals use their gaze to guide the attention of others (Bayliss et al., 2013). A gaze-leading task was originally developed by Bayliss et al. (2013) to inspect whether joint attention could also be stimulated through interactions in a computer-based environment. In the task, participants were shown two objects on the screen, one placed on the left and one placed on the right. In the middle of the objects was an avatar face that would correspond to the participant's action. To perform the task, participants were asked to choose one of the objects. Correspondingly, the eyes of the avatar face were manipulated either to look at the participants' chosen object (following behaviour) or to look at the other object (unfollowing behaviour).

The manipulation of avatar eye movement affected participants' responses to the task (Bayliss et al., 2013). Specifically, the measured responses were participants' return-to-face saccades after choosing one of the objects. Return-to-face saccades refer to the eye movements that participants made when they shifted their focus from the chosen object back to the avatar's face (Bayliss et al., 2013). In the task of Bayliss et al. (2013), participants were also asked to redirect their gaze toward the centre screen (the avatar face) as signalling their readiness for the subsequent trial. The duration of these saccades was served as an indicator of delayed response latency that had influenced by the manipulated conditions. Particularly, Bayliss et al. (2013) found a delay in participants reorientating their gaze towards the avatar face when the avatar did not follow their choice. This finding has opened significant avenues for further research, highlighting the importance of gaze interactions in joint attention.

**Gaze-Leading Task in HRI**

In an advancement of the previous study, Willemse et al. (2018) focused on the Human-Robot Interaction (HRI) paradigm. Unlike the previous study, which used a human face, Willemse et al. (2018) used a robot face as the avatar. In their study, they used a single robot face while demonstrating it twice to their participants, and declared that it was two 'different' robots with distinct dispositions and names. Two dispositions were defined: joint and disjoint. A robot with joint disposition would mostly follow the participant's choice, to look at the chosen object. Vise versa, a disjoint disposition robot would mostly exhibit unfollowing behaviour to look at the other object.

To salient the distinction between the dispositions, Willemse et al. (2018) introduced variability in the robot's gaze behaviour. In their approach, the joint robot would look at the participant's chosen object (following behaviour) in 80% of the trials; while in the remaining 20% of the trials, it would look at the other object (unfollowing behaviour). Vise versa, the reversed proportion (20% following and 80% unfollowing) was applied to the disjoint disposition robot.

Through this setup, they conducted the gaze-leading task and found that the manipulation of the robots' dispositions did affect participants' reactions. Generally, participants took a shorter time to return their gaze towards the joint robot compared to the disjoint robot. Moreover, they also collected the participants' subjective ratings about the likability and human likeness of the two robot dispositions. The results showed a preference for the joint robot over the disjoint one. This led to the conclusion that the attribution of the robots' dispositions can be learned through eye-gaze interaction and will potentially affect the preference towards the favourable robot disposition (Willemse et al., 2018).

Both Bayliss et al. (2013) and Willemse et al. (2018) observed an increased latency in participants' return-to-face saccade under the condition that the robot did not look at the chosen object (unfollowing behaviour) compared to when the robot looked (following behaviour). Further investigation by Willemse et al. (2018) revealed that return-to-face saccade was not only dependent on the robot's gaze behaviours in the trials (following, unfollowing) but also influenced by the attribution of robot dispositions (joint, disjoint). However, the specific interaction effect between these two variables and how they contribute to the latency remains unclear. For example, a study suggested that people might react drastically when faced with unexpected events, triggering an alert response (Dungan et al., 2016). Therefore, it is suspected that participants might react differently when a robot exhibits behaviour that is not expected. For instance, a robot with a joint disposition will typically follow the participant's choice, however, on occasion, it suddenly looks at the other objects. The unexpected unfollowing behaviour that occurred on a typical joint robot might stimulate a quicker response for participants to reorientate their gaze towards the robot's face. This raises the question of whether the interaction between the following behaviour and the attributed disposition will affect the latency in participants' return-to-face saccade.

**Current Study Aims**

The current study aims to inspect the joint attention mechanism under a gaze-leading task paradigm. Previous studies showed that the use of a robot face in the gaze-leading task not only revealed that joint attention can be initiated in a Human-Robot Interaction (HRI) environment but also revealed that the robots' onset gaze behaviour and its attributed dispositions matter. To investigate whether these two variables will interact and thus stimulate different reactions from participants, the current study will partially replicate the gaze-leading task from Willemse et al. (2018). The same setting will be used, but the current study will incorporate two different robot faces as stimuli.

Additionally, the current study will be conducted through a laptop and mouse device, with participants indicating their area of interest by mouse-clicking the stimuli displayed on the screen. A recent study by Willemse et al. (2022) employed a similar gaze-leading task using mouse clicks as an indicator of attention shifts and found comparable results to those obtained using eye-tracking. Specifically, participants exhibited quicker reactions, as evidenced by shorter durations of clicking back to the avatar face who looked consistently to their chosen object (following behaviour) compared to those who looked away (unfollowing behaviour). This finding suggests that similar attentional mechanisms may underlie both hand movements (mouse clicks) and eye movements, supporting the use of mouse clicking as a valid alternative to eye tracking in experimental setups. Moreover, utilizing a laptop and mouse setup may offer advantages such as cost-effectiveness, quicker setup time, and simplicity compared to using eye-tracking equipment. Thus, it is considered as a more feasible and compatible approach for the current study.

Apart from the gaze-leading task, the current study will also be interested in participants' subjective preferences of the attributed robot dispositions. Following the previous study, surveys will collect participants' subjective ratings about the robots' likability and human likeness, to determine their preferences between the joint or disjoint robot disposition throughout the interaction in the task. Lastly, two related hypotheses of the current study are shown below:

1. Participants will exhibit a quicker return-to-face saccade in response to unexpected unfollowing behaviour from a robot with an attributed joint disposition compared to

an expected unfollowing behaviour from a robot with an attributed disjoint disposition.

2. Participants will rate the robot with a joint disposition as more likeable and more human-like compared to the robot with a disjoint disposition.

# Method

## Participants

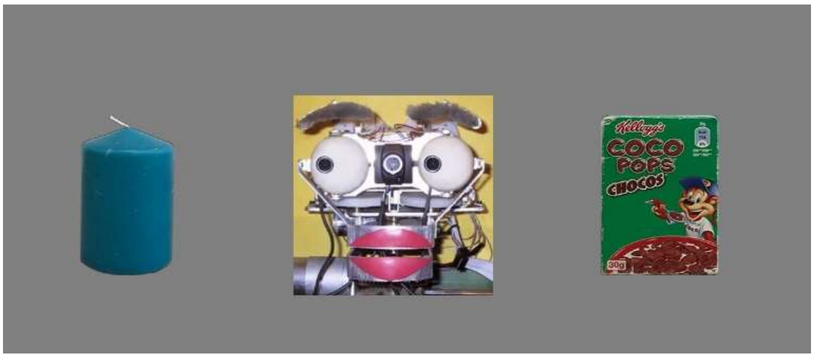
A total of 40 participants (26 females, 14 males, Age $M = 23.92$, $SD = 11.31$) were recruited via snowballing sampling through friends and family relatives. It was expected that the relationship between the researcher and the participants would not affect the study result. On the other hand, it helped to trace back the participants' responses to the follow-up survey. There was no limitation on the ages, nationalities, and personal traits to participate in the current study. However, participants were required to have corrected-to-normal vision. The current study has been approved by the BMS Ethics Committee of the University of Twente (request nr. 240251). All participants received the study information sheet and were given the consent to take part in the study. The study procedures were also aligned with the ethical requirements and well documented.

## Study Design and Materials

The current study used two instruments to collect data: a gaze-leading task and post-task surveys. The gaze-leading task was previously developed and programmed by using PsychoPy version 2023.2.3 (Peirce et al., 2019). For the current study, the task was adapted with compatible stimuli, including two robot faces and eight pairs of object pictures (see Appendix A). To stimulate the interaction between participants and the robot, the task was designed to require participants to perform the task by choosing one preferred object from two options. A robot face was presented in the centre of the screen, with the two objects displayed on each side (see Figure 1). The eyes of the robot were edited to create an impression of shifting gaze direction, which was also used to manipulate the robot's gaze behaviours, either to look at the same object as the participant selected (following behaviour) or the other object (unfollowing behaviour).

Additionally, post-task surveys were created in Qualtrics per robot to gather participants' perceptions regarding the robots. Consistent with a previous study from Willemse et al. (2018), 10 items were selected from the Likability and Anthropomorphism series of the Godspeed questionnaire, to include in the surveys. Responses were collected as the ratings for each item on a 5-point scale.

**Figure 1**




*Note*. The gaze-leading task presented in PsychoPy. Figure illustrating a practice trial with a robot face presented in the centre of the screen and two objects placed on each side (left and right). The eye of the robot is looking at the left side, which presents a response (following or unfollowing behaviour) after the participant selects one of the objects.

**Procedure**

Participants were individually recruited for the study and seated in front of the researcher's laptop upon arrival. They were provided with a digital study information sheet and a consent form, which they completed to indicate their agreement to participate. After obtaining consent, participants were introduced to the PsychoPy platform and instructed to follow on-screen instructions to complete the task. They were asked to select one of the displayed objects by mouse clicking and thus, click back on the robot's face to proceed to the next trial. All their mouse-clicking responses were recorded.

The session began with a practice task with eight trials guided by the researcher to ensure participants were familiar with the procedure. The presented stimuli in the practice task would not be used in the following main task. After the practice session, participants proceeded to complete the main task independently, with the researcher available nearby for assistance as needed. Scheduled breaks were provided according to instructions displayed on-screen.

To counterbalance the conditions, the dispositions of the robot (joint or disjoint) were manipulated. Half of the participants experienced Robot A with a joint disposition and Robot B with a disjoint disposition, while the other half experienced the reverse. Additionally, the current study employed an 80/20 probability approach to introduce variability in the robot’s gaze behaviour. Specifically, the joint disposition robot followed the participant's choices (typical behaviour) 80% of the time and did not follow (unexpected behaviour) 20% of the time, whereas the disjoint disposition robot exhibited the opposite pattern. In total, each participant experienced 160 trials, with 128 trials reflecting the robot's expected behaviour and 32 trials reflecting unexpected behaviour. This design ensured that any observed effects were due to the manipulations of disposition and gaze behaviour rather than specific characteristics of the robots, while also simulating realistic interactions by incorporating both typical and unexpected behaviours.

After completing the task, participants proceeded to complete post-task surveys. They were free to leave once these surveys were finished.

**Data Analysis**

All data analysis was conducted using the statistical software Rstudio (version 2023.03.0). R scripts were attached in Appendix II and III. Raw data from the PsychoPy platform were cleaned to include relevant variables such as Participant number, Reaction Times (RTs) for return-to-face saccade responses, Robot Dispositions (joint or disjoint) and gaze behaviour (followed or unfollowed). The data of RTs was previewed and proceed to remove the outliers to maintain data integrity. Firstly, the ranges of lower than 100ms and greater than 2000ms were considered outliers, which are deemed to be irrelevant to reflect meaningful reactions (Kvalsvik, 2024)). Further, Cook's distance method was employed to identify influential data points, which were subsequently removed from the dataset. In total, the responses from 736 trials were identified as outliers and thus removed from the dataset.

To test the hypothesis that participants will exhibit a quicker return-to-face saccade in response to unexpected unfollowing behaviour from a robot with an attributed joint disposition compared to an expected unfollowing behaviour from a robot with an attributed disjoint disposition, the average RTs were first compared across different conditions. Subsequently, a linear mixed effects regression analysis was conducted. The independent variables included robot gaze behaviour (followed vs. unfollowed) and robot disposition (joint vs. disjoint), with return-to-face saccade Reaction Times (RTs) as the dependent variable. The regression model examined the independent effects of these variables, as well as their interaction effects, to explore how the combination of robot gaze behaviour and disposition influences the RTs.

Additionally, to investigate whether participants' perceptions of robots vary based on their disposition, data from Qualtrics on likability and anthropomorphism ratings were analysed. Mean scores for each rating were computed and compared between robots with joint and disjoint dispositions. Shapiro-Wilk tests were employed to assess the normality of mean rating scores in each condition. Depending on the normality assessment, either parametric (two-sample t-tests) or non-parametric (Wilcoxon signed-rank test) analyses would be used to compare mean scores across disposition conditions. This approach aimed to test the hypothesis that participants would rate robots with a joint disposition as significantly more likeable and human-like compared to those with a disjoint disposition.

# Results

## Reaction Time Analysis

To test the hypothesis that participants will exhibit a quicker return-to-face saccade in response to unexpected unfollowing behaviour from a robot with an attributed joint disposition compared to an expected unfollowing behaviour from a robot with an attributed disjoint disposition, the average RTs were compared across different conditions Table 1 presents quantitative data showing the mean RTs for each condition. For joint robots, the difference in mean RTs between followed (typical behaviour) and unfollowed (unexpected behaviour) is 49ms. In contrast, for the disjoint robot, the difference between the two behaviours is 26ms. Overall, the mean RTs were slightly lower when robots exhibited behaviours that were opposite to their typical disposition. These findings suggest that participants tend to elicit shorter RTs when they encounter the robot behaving contrary to their attributed disposition.

**Table 1**

*Mean reaction time for each condition*

| Condition | Behaviour | Mean_RT |
|---|---|---|
| Joint-Followed | Typical | 856 |
| Joint-Unfollowed | Unexpected | 807 |
| Disjoint-Followed | Unexpected | 829 |
| Disjoint-Unfollowed | Typical | 855 |

A linear mixed-effects regression analysis was performed, using the RTs for participants' return-to-face saccade responses as the dependent variable with the two types of robot dispositions and two types of following behaviours as independent variables. The fixed effects for the linear mixed effects model are demonstrated in Table 2 and the visual representation of the estimated mean RT for each condition is presented in Figure 2.

**Figure 2**

*Plot for fixed effects of Reaction Time, Robot Disposition and Following Behaviour*

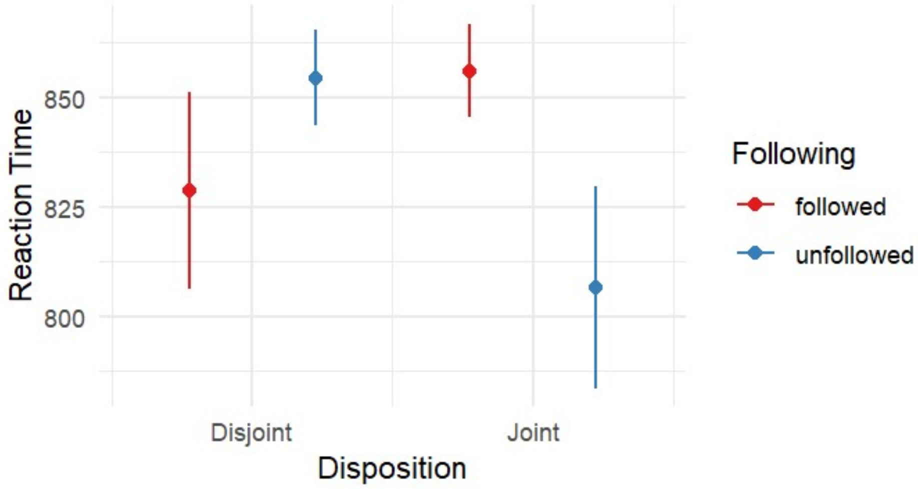



**Table 2**

*Fixed effects of LMM for Reaction Time, Disposition, Following Behaviour*

| Parameter Name | Estimate | Std. Error | P-value |
|---|---|---|---|
| (Intercept) | 828.78 | 11.49 | < 0.001 |
| Disposition Joint | 27.35 | 12.73 | 0.325 |
| Following unfollowed | 25.76 | 12.75 | 0.353 |
| Disposition Joint: Following unfollowed | -75.29 | 18.19 | 0.009 |

In Table 2, the robot disposition with joint condition estimated an increased mean of 27ms in RTs compared to disjoint robots. This means that participants took a longer time to reorient their gaze back to the robot's face when they encountered the joint robot. However, this difference was found non-significant ($p = 0.32$).

Moreover, the parameter 'Following unfollowed' also observed an increased mean of 25ms in RT when the robot exhibited unfollowed gaze behaviour compared to when it followed. This means that participants took a longer time to reorient their gaze back to the robot's face when they encountered the robot that looked at the other object than their choice. However, this difference was also found non-significant ($p = 0.35$).

Lastly, the parameter "Disposition Joint: Following unfollowed" underscores the interaction effect between robot dispositions and following behaviours on the reaction times. It means that in the condition of a joint disposition robot to exhibit unfollowed gaze behaviour, a significantly lower estimate of – 75ms in RT ($p$ = 0.009, < 0.05) was found. This indicated that participants returned to the robot face more quickly whenever they encountered a joint disposition robot that did not follow their choice.

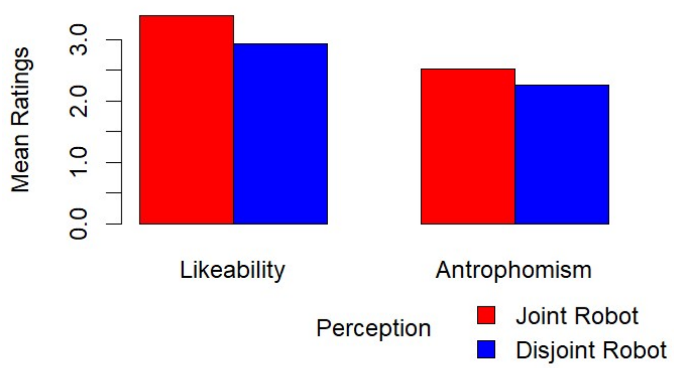
In brief, these findings indicate that participants' reaction times were influenced by the interaction between robot disposition and following behaviour, despite non-significant differences observed between individual conditions.

**Subjective Ratings Analysis: Likability and Anthropomorphism**

To investigate whether participants' subjective preferences of the robots varied based on their dispositions (joint or disjoint), mean scores of the likability and anthropomorphism ratings were calculated and compared between the dispositions. In Figure 3, the mean likability score for the joint robot ($M$ = 3.39, $SD$ = 1.04) was slightly higher compared to the disjoint robot ($M$ = 2.92, $SD$ = 1.16). Moreover, for the anthropomorphism scores, the mean scores for joint robots ($M$ = 2.52, $SD$ = 0.98) were again slightly higher than the disjoint robots ($M$ = 2.26, $SD$ = 0.95).

**Figure 3**

*Mean ratings for Joint and Disjoint robot*

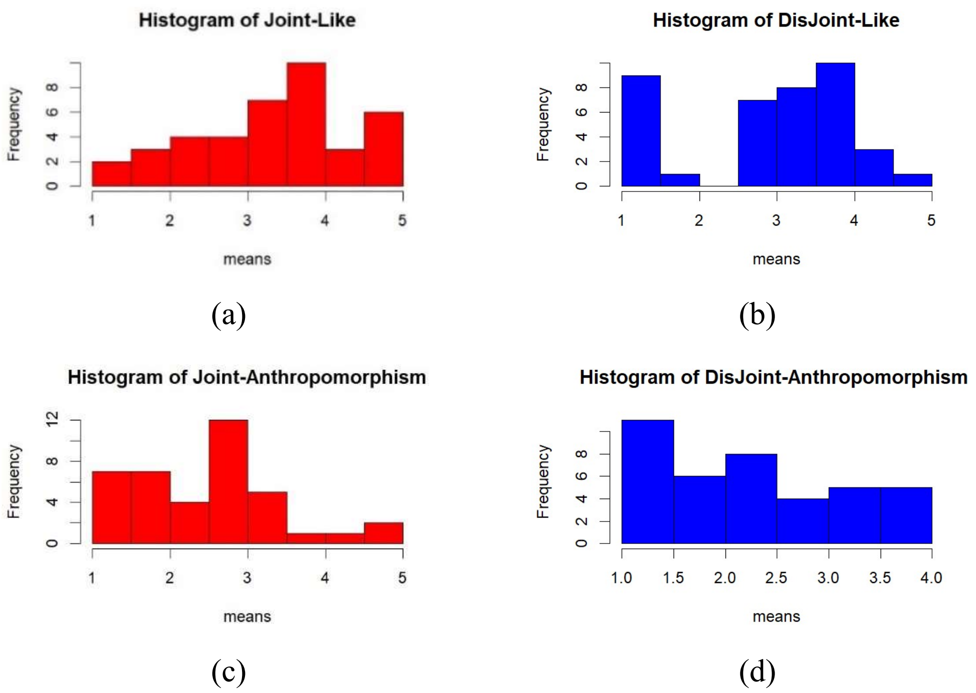


To assess the normality of mean rating scores for each condition, Shapiro-Wilk tests were conducted. The data of participants' rating anthropomorphism scores significantly deviated from a normal distribution for both the joint robot ($W = 0.95$, $p = 0.07$) and the disjoint robot ($W = 0.93$, $p = 0.01$). For the likability rating scores, only the data for the joint robot did not significantly deviate from a normal distribution ($W = 0.96$, $p = 0.16$), but the data for the disjoint robot significantly deviated from a normal distribution ($W = 0.91$, $p < 0.001$).

In addition, Figure 4 illustrates the histogram distribution for each condition. While overall distributions were non-normal, discernible trends still can be observed. Specifically, Figures 3(b) and 3(d) indicate that a higher proportion of participants rated both likability and anthropomorphism scores as '1' for the robot attributed with a disjoint disposition. This suggests a tendency among participants to perceive the robot with disjoint behaviour as less likeable and less human-like compared to the joint disposition robot.

**Figure 4**

Histograms for Likeability and Anthropomorphism rating scores for Joint vs Disjoint robots



*Note.* Figure 4(a) shows the histogram for the likeability ratings of the joint disposition robot. (b) likeability ratings of the disjoint disposition robot. (c) Anthropomorphism ratings of the joint disposition robot. (d) Anthropomorphism ratings of the disjoint disposition robot.

Due to the violation of the normality assumption, non-parametric tests were employed to analyse the data. Wilcoxon signed-rank tests were conducted to compare the mean scores of both likability and anthropomorphism subjective ratings between the robots with joint and disjoint dispositions. The results indicated no significant median difference in likability ratings between the joint robot and the disjoint robot ($V = 416$, $p = 0.17$). Similarly, there was no significant median difference in anthropomorphism ratings between the joint robot and the disjoint robot ($V = 410$, $p = 0.19$). These findings suggest that participants' subjective ratings did not differ significantly between the robots with joint and disjoint dispositions.

## Discussion

The current study aimed to investigate the joint attention mechanism in Human-Robot Interaction (HRI) using a gaze-leading task paradigm. Specifically, it was aimed to explore how robot gaze behaviours (following or unfollowing) interact with the attributed dispositions (joint or disjoint) to influence participants' reaction times in return-to-face saccade responses. Additionally, the study was interested in examining participants' subjective perceptions of likability and human likeness towards robots with the two different dispositions.

### Reaction Times

The primary hypothesis suggested that participants would demonstrate quicker return-to-face saccades in response to unexpected unfollowing behaviour from the robots with a joint disposition, compared to expected unfollowing behaviour from the robots with a disjoint disposition. This hypothesis was based on the expectation that robot disposition and gaze behaviour will interact and influence participants' reactions in the gaze-leading task.

The current study's findings confirmed that participants exhibited lower reaction times (RTs) when encountering unexpected robot behaviour compared to typical behaviour. Specifically, this difference was more pronounced for the joint robot compared to the disjoint robot. The results from the linear mixed-effects regression model supported a significant interaction effect, highlighting substantial differences between conditions. This suggests that participants reacted more swiftly, returning their gaze to the robot's face faster when robots exhibited gaze behaviour that was opposite to their expected disposition.

Moreover, these findings could also imply that participants were motivated to establish joint attention with the robot that typically followed their gaze (joint disposition). Consequently, when the robot did not follow its gaze, participants showed a heightened response, indicating a strong reaction to deviations from the expected following behaviour. This underscores the dynamic interplay between participants' engagement with the robot and the robot's behaviour, influencing their responses to reengage with the robot.

**Subjective Preferences**

Another aim of the current study was to investigate whether participants' subjective preferences of the robots varied based on the attributed dispositions (joint or disjoint), specifically focusing on the participants' subjective ratings for likability and anthropomorphism. Initial analysis showed slightly higher mean scores for likability and anthropomorphism ratings for joint robots compared to disjoint robots. However, further non-parametric tests revealed no significant median differences in both likability and anthropomorphism ratings for the joint and disjoint robot dispositions. These results did not support the current hypothesis, showing that participants did not rate the robot with a joint disposition as more likeable and more human-like compared to the robot with a disjoint disposition.

However, one potential finding to be noticed is when assessing the rating distribution across the conditions, a higher proportion of participants had rated both likability and anthropomorphism scores as '1' for the disjoint disposition robot. This hints at a lower preference for the robots with disjoint dispositions as they are less likeable and less human-like. One possible explanation is that the simplistic robot design in the current study, which only makes changes in eye area without changing other facial characteristics might have made participants feel uncomfortable, thereby impacting their perceptions during the interactions and leading to low rating scores. Future studies should take into this concern and lean towards using more comprehensive and nuanced robot designs to better understand how physical appearance and behavioural cues would influence human perceptions and preferences.

**Limitations and Recommendations**

Several limitations of this study should be acknowledged. First, the use of a laptop and mouse device may not fully replicate the dynamics of real-world Human-Robot Interaction (HRI) scenarios. Research by Kvalsvik (2024) has suggested that measuring reaction times via mouse clicks may not effectively capture subtle differences in joint attention mechanisms, as motor responses can differ from actual gaze-following behaviours. Although using a laptop and mouse offers advantages such as cost-effectiveness and accessibility, eye-tracking equipment is recommended for more accurately capturing participants' nuanced responses in HRI scenarios (Kvalsvik, 2024). Future studies should still consider incorporating eye-tracking technology to enhance measurement precision if it is accessible.

Moreover, the use of a digital platform to present the gaze-leading task to participants may underestimate the complexity of social interactions between the robot and the participant. In the current study, participants only encountered minor eye-gaze direction changes from the robots, which might overlook other mechanisms that could create a stronger joint attention connection. To better simulate the natural interactions, future studies could consider employing more immersive interfaces, such as virtual reality or physical robot interactions. This approach could provide a more comprehensive understanding of how joint attention mechanisms operate in more realistic and engaging HRI settings.

Besides that, the lengthy and pretty high frequency of trials in the current gaze-leading task may induce participants to generate automated clicking behaviours. This might reduce the task's sensitivity to detect attention shifts. As participants engage repeatedly over an extended period, they may develop habitual responses to the task stimuli. Consequently, the study might potentially overlook the nuanced shifting in attention that it aims to capture. Therefore, future studies should consider a shorter and more streamlined design to minimize the likelihood of automated behaviours and maintain sensitivity to subtle changes in attention and interaction dynamics.

Lastly, the design of the robot faces to create the impression of gaze direction changes played a crucial role in participant perception and interaction. The simplistic approach in the current study, which only makes changes in eye area without changing other facial characteristics, led some participants to feel uncomfortable and report that the robots' behaviour seemed unnatural. This discomfort may have impacted their willingness to engage fully or respond authentically, thus influencing their initial perceptions and comfort levels during the interactions. Future studies should consider incorporating more natural and varied facial expressions to enhance participant comfort and engagement.

## Conclusion

In conclusion, this study supported the hypothesis, revealing significantly lower reaction times for unexpected behaviours, particularly pronounced with joint disposition robots. The subjective preferences for robot likability and anthropomorphism did not vary significantly by robot dispositions but suggested a slight preference for joint disposition robots. Future research should address limitations by using more immersive technologies and refining experimental designs to enhance understanding of human-robot social interactions and improve user experiences in various contexts.

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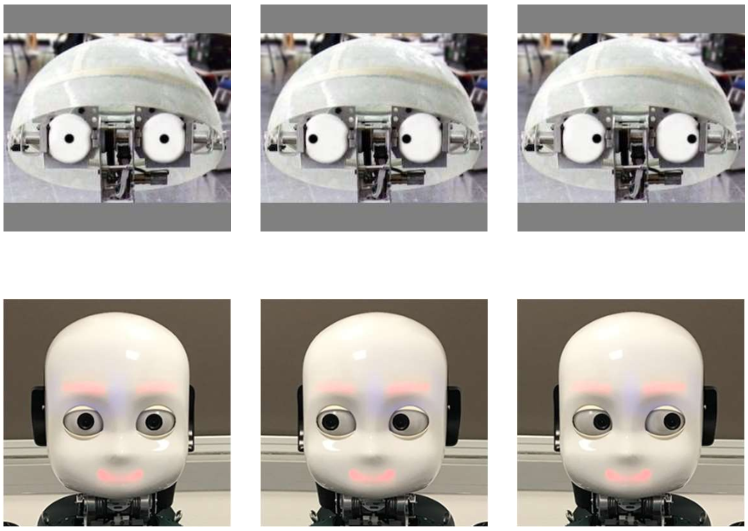
Willemse, C., Marchesi, S., & Wykowska, A. (2018). Robot faces that follow gaze facilitate attentional engagement and increase their likeability. *Frontiers in Psychology*, *9*(FEB), 317827. https://doi.org/10.3389/FPSYG.2018.00070/BIBTEX

## Appendix

### Appendix I: Stimuli of Gaze-leading Task

**Robot Faces**



(1) (2) (3)

*Note*. Robot A and Robot B with the three eye movements: (1) looking straight ahead, (2) looking to the left, and (3) looking to the right.

**Object Pictures**

*Note*. These object pictures were adapted from the study by Willemse et al. (2018), represented as the objects which the robots can interact with, and were grouped into eight pairs based on their similar shapes and colours.

**Appendix II: R Markdown of Gaze-Leading Task Data Analysis**

# RDATAanalyse.R

kayaa

2024-06-23

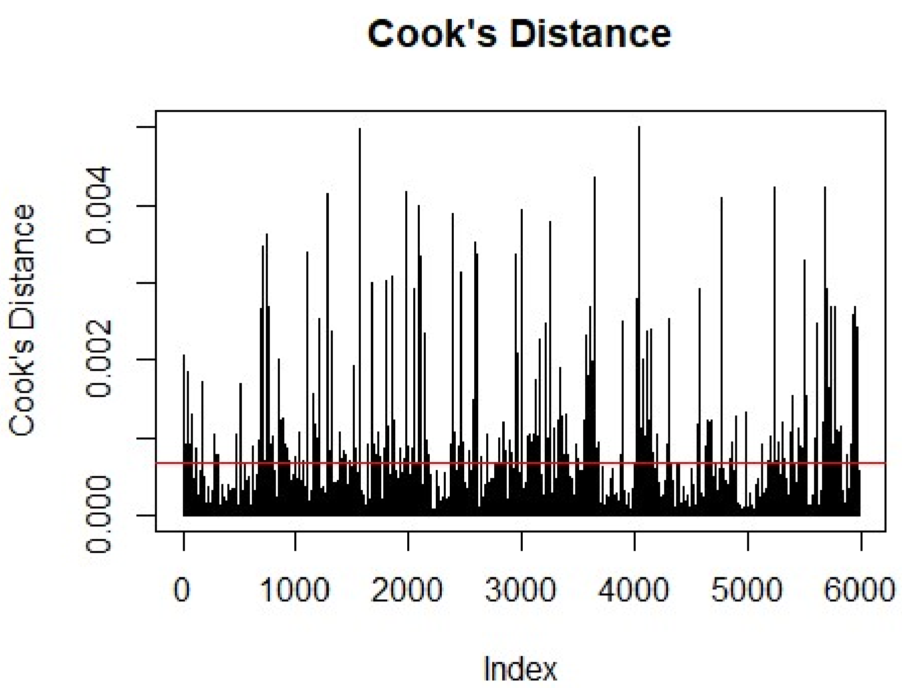
```
## tidyverse
library(tidyverse)

## Warning: package 'tidyr' was built under R version 4.3.3

## Warning: package 'dplyr' was built under R version 4.3.3

## Warning: package 'stringr' was built under R version 4.3.3

## ── Attaching core tidyverse packages ──────────────────────── tidyverse
 2.0.0 ──
## ✓ dplyr     1.1.4     ✓ readr     2.1.4
## ✓ forcats   1.0.0     ✓ stringr   1.5.1
## ✓ ggplot2   3.4.2     ✓ tibble    3.2.1
## ✓ lubridate 1.9.2     ✓ tidyr     1.3.1
## ✓ purrr     1.0.1
## ── Conflicts ────────────────────────────────────────── tidyverse_confl
icts() ──
## ✕ dplyr::filter() masks stats::filter()
## ✕ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force
all conflicts to become errors

## data manipulation
library(openxlsx)

## Warning: package 'openxlsx' was built under R version 4.3.3

## other
library(lme4)

## Loading required package: Matrix
##
## Attaching package: 'Matrix'
##
## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

library(ggeffects)

## Warning: package 'ggeffects' was built under R version 4.3.3

#imprort ALL RAW data
P1 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
data/ExperimentRAW/1.csv')
P2 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
```

```
data/ExperimentRAW/2.csv')
P3 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
data/ExperimentRAW/3.csv')
P4 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
data/ExperimentRAW/4.csv')
P5 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
data/ExperimentRAW/5.csv')
P6 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
data/ExperimentRAW/6.csv')
P7 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
data/ExperimentRAW/7.csv')
P8 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
data/ExperimentRAW/8.csv')
P9 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
data/ExperimentRAW/9.csv')
P10 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/10.csv')
P11 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/11.csv')
P12 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/12.csv')
P13 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/13.csv')
P14 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/14.csv')
P15 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/15.csv')
P16 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/16.csv')
P17 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/17.csv')
P18 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/18.csv')
P19 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/19.csv')
P20 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RAW
 data/ExperimentRAW/20.csv')
P101 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/101.csv')
P102 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/102.csv')
P103 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/103.csv')
P104 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/104.csv')
P105 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/105.csv')
P106 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/106.csv')
P107 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/107.csv')
P108 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/108.csv')
P109 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
```

```
W data/ExperimentRAW/109.csv')
P110 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/110.csv')
P111 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/111.csv')
P112 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/112.csv')
P113 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/113.csv')
P114 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/114.csv')
P115 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/115.csv')
P116 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/116.csv')
P117 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/117.csv')
P118 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/118.csv')
P119 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/119.csv')
P120 <- read.csv('C:/Users/kayaa/OneDrive - University of Twente/Thesis/RA
W data/ExperimentRAW/120.csv')


#structure the data, leave only usable variables
P1 <- P1[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P2 <- P2[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P3 <- P3[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P4 <- P4[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P5 <- P5[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P6 <- P6[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P7 <- P7[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P8 <- P8[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P9 <- P9[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P10 <- P10[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P11 <- P11[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P12 <- P12[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P13 <- P13[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P14 <- P14[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
```

```
P15 <- P15[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P16 <- P16[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P17 <- P17[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P18 <- P18[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P19 <- P19[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P20 <- P20[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P101 <- P101[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P102 <- P102[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P103 <- P103[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P104 <- P104[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P105 <- P105[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P106 <- P106[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P107 <- P107[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P108 <- P108[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P109 <- P109[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P110 <- P110[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P111 <- P111[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P112 <- P112[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P113 <- P113[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P114 <- P114[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P115 <- P115[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P116 <- P116[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P117 <- P117[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P118 <- P118[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P119 <- P119[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)
P120 <- P120[9:168,] %>%
  select(returnRT,Following,Face,Condition,participant,list,trials.thisN)

#merge all the data
```

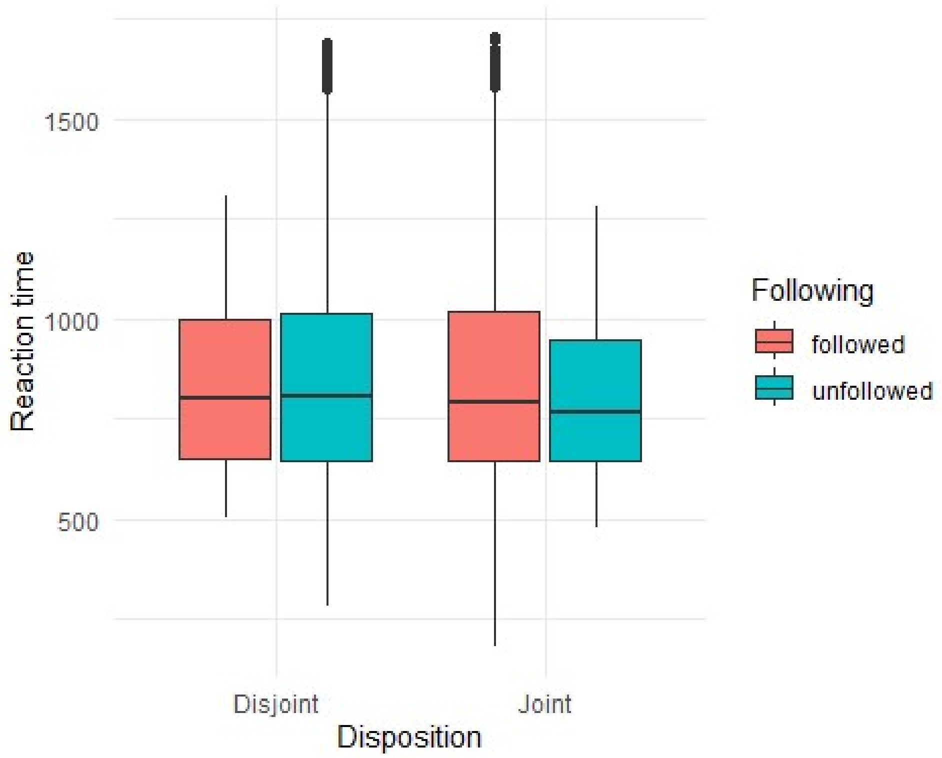
```
ALLdata <- rbind(P1,P2,P3,P4,P5,P6,P7,P8,P9,P10,P11,P12,P13,P14,P15,P16,P1
7,P18,P19,P20,
                 P101,P102,P103,P104,P105,P106,P107,P108,P109,P110,P111,P1
12,P113,P114,
                 P115,P116,P117,P118,P119,P120)

ALLdata$trials <- ALLdata$trials.thisN
ALLdata$disposition <- ALLdata$Condition
ALLdata <- separate(ALLdata, col = disposition, into = c("Disposition", "S
econdPart"), sep = "-")
ALLdata$SecondPart <- NULL
ALLdata$trials.thisN <- NULL

### Identify outliers
## Specific range
outliers <- ALLdata$returnRT < 100 | ALLdata$returnRT > 2000
ALLdata_clean <- ALLdata[!outliers, ]

## Cook's distance Method
# Fit the initial linear model
model <- lm(returnRT ~ Disposition * Following, data = ALLdata_clean)

# Calculate Cook's distance
cooksd <- cooks.distance(model)

# Plot Cook's distance
plot(cooksd, type="h", main="Cook's Distance", ylab="Cook's Distance", xla
b="Index")
abline(h = 4 / length(ALLdata_clean$returnRT), col = "red")  # Common thre
shold
```



```
# Identify high Cook's distance points
influential_points <- which(cooksd > (4 / length(ALLdata_clean$returnRT)))
print("Influential points (by observation index):")

## [1] "Influential points (by observation index):"

print(influential_points)

##     9    32    44    51    55    57    86    91    94   115   119   158 
  160 
##     1    18    29    35    39    41    59    62    65    84    87   119 
  121 
##   451   461   521   531   551  1012  1112  1412   262   372   533   923 
  424 
##   163   164   170   171   172   282   283   286   298   309   479   515 
  623 
##   854  1004  1174  1224  1364  1424  1584  1664  1018  1118  1218  1617 
  265 
##   662   675   691   695   708   714   730   738   741   742   743   747 
  753 
##   335   425   475   525   775   919  1375  1575   920  1120  1619   376 
  426 
##   760   766   767   770   790   803   847   865   876   878   879   893 
  897 
##   786   806 15110   367   647   997  1028  1067  1107  1487   218   328 
  528 
##   929   931   994  1035  1063  1098  1101  1105  1109  1147  1176  1186 
 1203 
##  1338  1408  1588  1688   949  1169 12113  1509  1640  5610  7910  8110 
11510 
##  1276  1283  1301  1310  1390  1411  1416  1443  1468  1505  1527  1529 
 1559 
## 12212  3611  4811  7911  9811 12311 14115 14411 15511  4512  6812  7712 
 8312 
##  1565  1635  1646  1671  1690  1711  1726  1729  1738  1779  1798  1806 
 1811 
##  8512 12612 13912 15012 15712  4413  9413  9913 13117 15613  1480  5214 
 6114 
##  1813  1851  1862  1873  1876  1919  1966  1971  2003  2027  2045  2079 
 2088 
##  7514  8114  8614 11414 11514 12314 12714 13514 14118 16014  4016  4516 
 6116 
##  2101  2107  2112  2135  2136  2143  2147  2154  2160  2179  2370  2375 
 2391 
##  6216  8616 11816 12916 14416 15516  4717  8317  9017  9917 10717 11717 
15817 
##  2392  2415  2445  2455  2470  2481  2533  2569  2576  2585  2593  2602 
 2643 
##  4918 14122 16018 16219 16818  4119  4619  6119  9221 11123 11319 14619 
15123 
##  2692  2781  2800  2802  2808  2840  2845  2857  2884  2903  2905  2938 
 2943 
## 15419 15819  1920  2220  5120  9920 11520 12020 13222 14124 14520 15222 
15820 
```

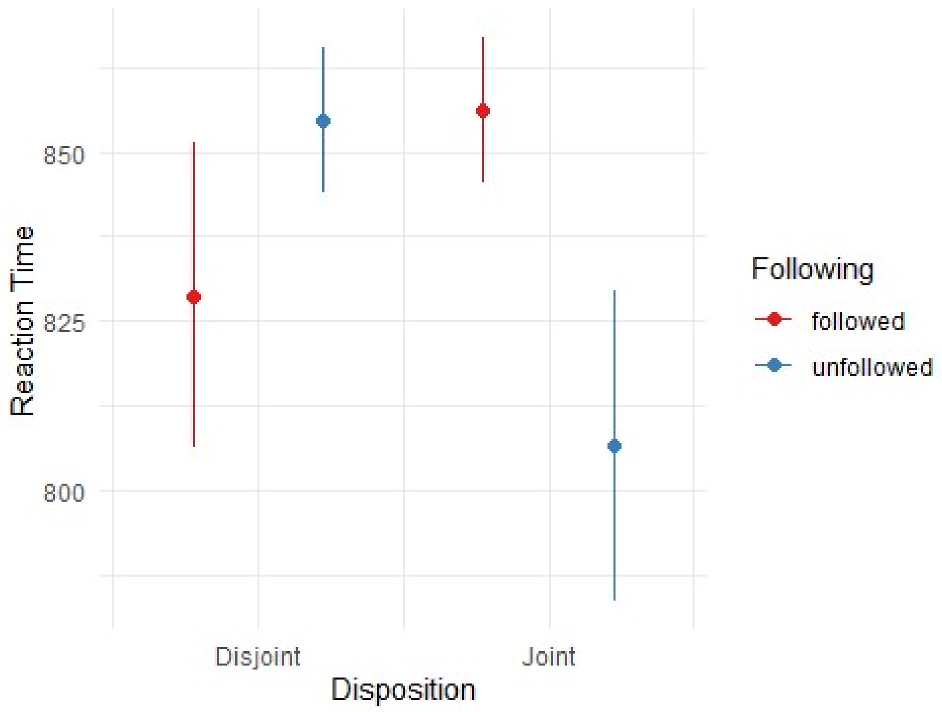
```
##  2946  2950  2967  2970  2998  3044  3057  3062  3073  3082  3086  3092 
  3097 
## 11105 12105 13105 14105  2021  2121  2821  3321  5421  5621  6121  6321 
  6421 
##  3109  3110  3111  3112  3115  3116  3120  3123  3143  3145  3149  3151 
  3152 
## 13021 13223 13321 13621 15821 14106  2322  5022  9522  9922 10126 10922 
 11922 
##  3210  3212  3213  3215  3236  3250  3256  3283  3327  3331  3333  3341 
  3350 
## 13022 13522 14422 16522  2523  9623 11523 10108 14108  2724  2824  3024 
  3224 
##  3361  3365  3374  3395  3414  3484  3503  3557  3561  3574  3575  3576 
  3578 
##  3424  3624  3724  3824  4124  4324  5624  6124  7524 10128 13128 13524 
  2226 
##  3580  3582  3583  3584  3585  3587  3599  3604  3617  3641  3669  3672 
  3871 
##  2726  3926 10132  1827  2127  2327  2427  2627  2727  3027  3327  3827 
  4027 
##  3876  3887  4015  4022  4024  4026  4027  4029  4030  4032  4035  4040 
  4042 
##  5127  5927  7027  7527  7727  9927 10727 11027 11133 12827 13027 15133 
 15229 
##  4050  4058  4069  4073  4075  4096  4102  4104  4105  4122  4123  4142 
  4143 
## 12134  2128  5528 15628 11136  8229  9929  9430  9930 11030 12530 13140 
  1931 
##  4161  4169  4202  4296  4311  4382  4399  4552  4557  4568  4582  4630 
  4636 
##  2431  3231  5131  7231  7631 16135 10142  8232  9143  9332 10332 10932 
 11032 
##  4641  4648  4664  4681  4685  4763  4770  4841  4850  4852  4862  4868 
  4869 
## 13532  6733  5334  6634 12334 14434 15734  3035  4435  6135  6235 10149 
 11035 
##  4892  4983  5124  5135  5183  5202  5214  5244  5258  5275  5276  5314 
  5322 
##  1836  2136  3736  5236  7536  9238  9836 12636 14036 14151 15336 15636 
 16736 
##  5387  5390  5406  5421  5443  5459  5465  5490  5504  5505  5515  5517 
  5528 
##  8437 10037 15239 11154  1838  1938  2538  2938  3138  3338  4738  5638 
  5838 
##  5601  5615  5667  5685  5687  5688  5694  5697  5699  5701  5715  5722 
  5724 
##  7038  7138  7338  8038  8338  8638 10438 11038 11155 11638 12155 13738 
 14738 
##  5734  5735  5737  5744  5747  5750  5768  5774  5775  5780  5785  5800 
  5809 
## 14156  5939  6739  9241 10157 11939 12839 13241 14839 
##  5836  5879  5887  5912  5921  5939  5947  5951  5965
```

```
# Create a new dataset excluding influential observations
ALLdata_cleaned <- ALLdata_clean[-influential_points, ]

# Plot Average RT for each face type and disposition
ggplot(ALLdata_cleaned, aes(x = Disposition, y = returnRT, fill = Followin
g)) +
  geom_boxplot() +
  labs(x = "Disposition", y = "Reaction time") +
  theme_minimal()
```




```
#Descriptive stats
ALLdata_cleaned %>% group_by(Condition) %>% summarise(mean_RT = mean(retur
nRT, na.rm = TRUE),
                                                       sd_RT = sd(returnRT, n
a.rm = TRUE),)

## # A tibble: 4 × 3
##   Condition           mean_RT sd_RT
##   <chr>                 <dbl> <dbl>
## 1 Disjoint-Followed      829.  210.
## 2 Disjoint-Unfollowed    855.  274.
## 3 Joint-Followed         856.  278.
## 4 Joint-Unfollowed       807.  202.

## Fit the initial linear model
model_2 <- lm(returnRT ~ Disposition * Following, data = ALLdata_cleaned)
summary(model_2)

##
## Call:
## lm(formula = returnRT ~ Disposition * Following, data = ALLdata_cleane
```

```
d)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -675.12 -202.12  -55.57  160.46  850.88
##
## Coefficients:
##                                      Estimate Std. Error t value Pr(>|t
|)
## (Intercept)                            828.78      11.49  72.101  < 2e-
16 ***
## DispositionJoint                        27.35      12.73   2.148   0.03
18 *
## Followingunfollowed                     25.76      12.75   2.021   0.04
33 *
## DispositionJoint:Followingunfollowed   -75.29      18.19  -4.139 3.55e-
05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 264.4 on 5660 degrees of freedom
## Multiple R-squared:  0.003305,   Adjusted R-squared:  0.002776
## F-statistic: 6.255 on 3 and 5660 DF,  p-value: 0.0003099

#ploting model
ggpredict(model_2, terms = c("Disposition", "Following")) %>%
  plot(dodge = 0.9) +
  labs(x = "Disposition", y = "Reaction Time", title = "") +
  theme_minimal()
```



**Appendix III: R Markdown of Qualtrics Data Analysis**

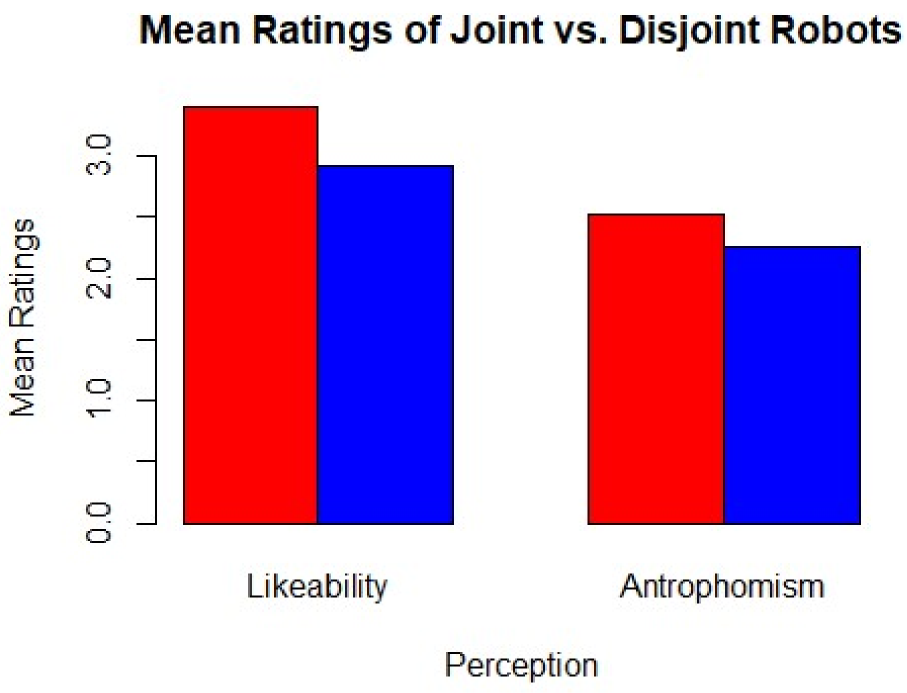
# SurveyAnalyse.R

kayaa

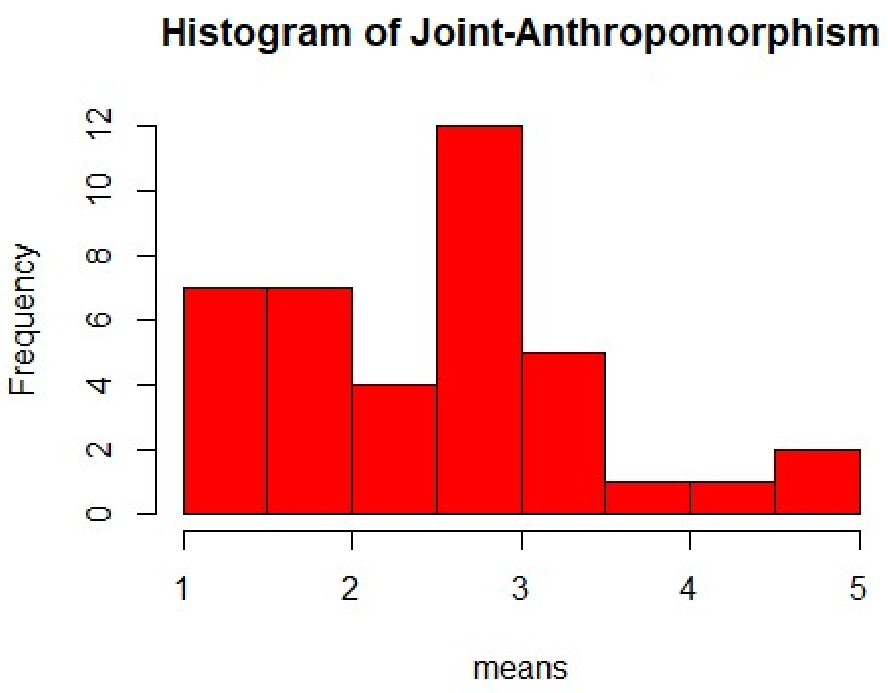
2024-06-18

```
library(tidyverse)

## Warning: package 'tidyr' was built under R version 4.3.3

## Warning: package 'dplyr' was built under R version 4.3.3

## Warning: package 'stringr' was built under R version 4.3.3

## ── Attaching core tidyverse packages ──────────────────────── tidyverse
 2.0.0 ──
## ✓ dplyr     1.1.4     ✓ readr     2.1.4
## ✓ forcats   1.0.0     ✓ stringr   1.5.1
## ✓ ggplot2   3.4.2     ✓ tibble    3.2.1
## ✓ lubridate 1.9.2     ✓ tidyr     1.3.1
## ✓ purrr     1.0.1
## ── Conflicts ────────────────────────────────────────── tidyverse_confl
icts() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force
all conflicts to become errors

library(openxlsx)

## Warning: package 'openxlsx' was built under R version 4.3.3

JIMdata <- read.csv("C:/Users/kayaa/OneDrive - University of Twente/Thesis
/RAW data/JIM.csv")
BOBdata <- read.csv("C:/Users/kayaa/OneDrive - University of Twente/Thesis
/RAW data/BOB.csv")

JIMdata$meanA <- rowMeans(JIMdata[2:6])
JIMdata$meanL <- rowMeans(JIMdata[7:11])

BOBdata$meanA <- rowMeans(BOBdata[2:6])
BOBdata$meanL <- rowMeans(BOBdata[7:11])

BOBdata <- BOBdata[BOBdata$Part != "1",]
JIMdata <- JIMdata[JIMdata$Part != "1",]

BOBdata <- BOBdata %>% select(Part,meanA,meanL)
JIMdata <- JIMdata %>% select(Part,meanA,meanL)

DisJointBob <- BOBdata %>% filter(Part %% 2 == 0)
JointJim <- BOBdata %>% filter(Part %% 2 != 0)
```

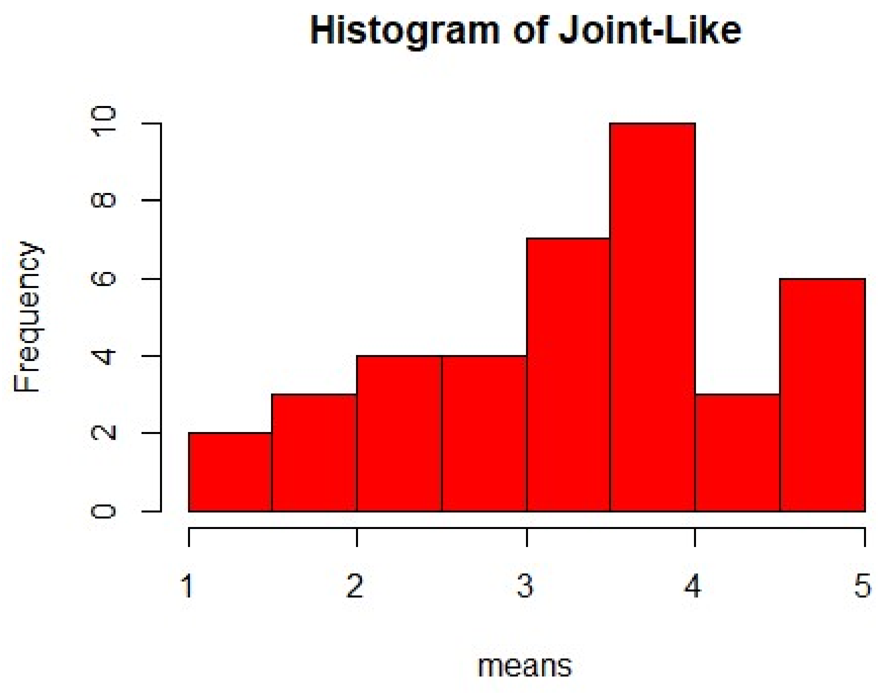
```
JointBob <- JIMdata  %>% filter(Part %% 2 == 0)
DisJointJim <- JIMdata %>% filter(Part %% 2 != 0)

Joint <- rbind(JointBob,JointJim)
DisJoint <- rbind(DisJointBob,DisJointJim)

# Descriptive data
mean(Joint$meanA)

## [1] 2.523077

mean(Joint$meanL)

## [1] 3.394872

mean(DisJoint$meanA)

## [1] 2.261538

mean(DisJoint$meanL)

## [1] 2.923077

sd(Joint$meanA)

## [1] 0.9836724

sd(Joint$meanL)

## [1] 1.047792

sd(DisJoint$meanA)

## [1] 0.9538331

sd(DisJoint$meanL)

## [1] 1.168549

# Mean values
means <- c(mean(Joint$meanA),
           mean(Joint$meanL),
           mean(DisJoint$meanA),
           mean(DisJoint$meanL))
# Plot the means
Joint_means <- c(mean(Joint$meanL),mean(Joint$meanA))
DisJoint_means <- c(mean(DisJoint$meanL), mean(DisJoint$meanA))

barplot(rbind(Joint_means, DisJoint_means), beside = TRUE,
        col = c("red", "blue"), main = "Mean Ratings of Joint vs. Disjoint
 Robots",
        xlab = "Perception", ylab = "Mean Ratings",
        legend.text = c("Joint Robot", "Disjoint Robot"),
        args.legend = list(x = "bottomright", bty = "n", inset = c(-0.10,
-0.75)),
        names.arg = c("Likeability", "Antrophomism"))
```



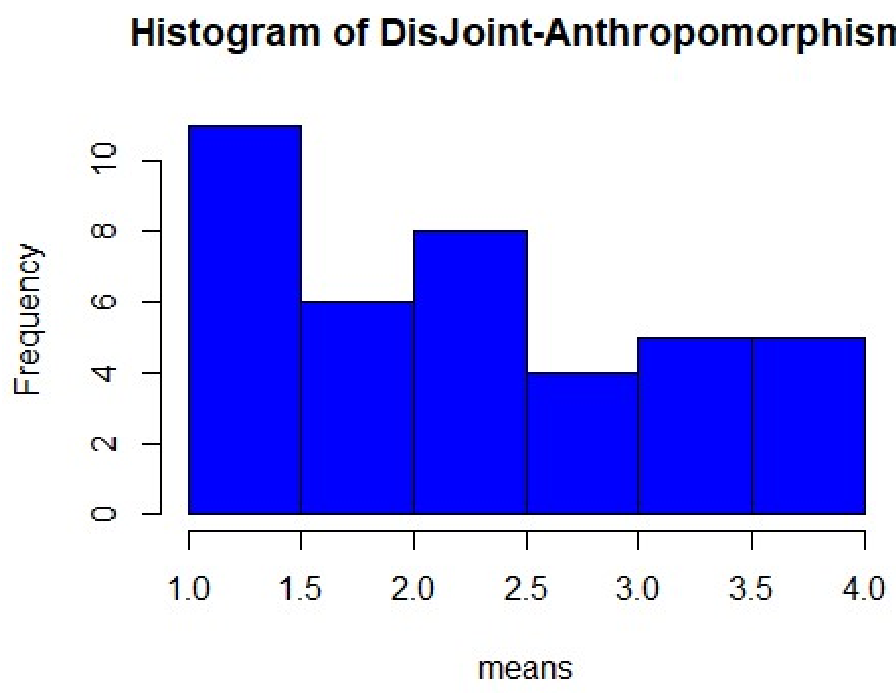

```
#plot
# Create a histogram
hist(Joint$meanA, main = "Histogram of Joint-Anthropomorphism", xlab = "me
ans", ylab = "Frequency", col = "red", border = "black")
```



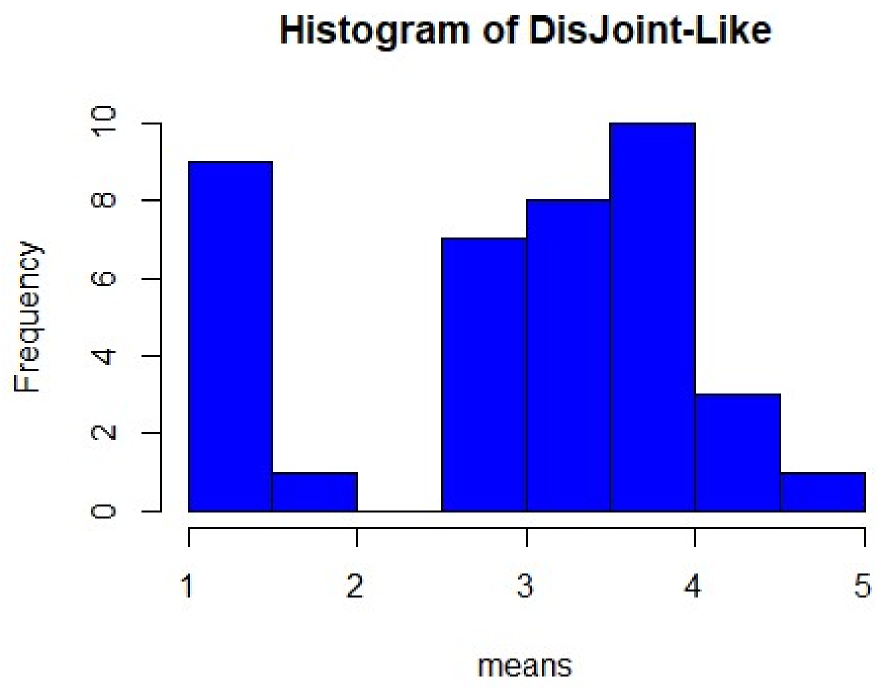

```
hist(Joint$meanL, main = "Histogram of Joint-Like", xlab = "means", ylab =
 "Frequency", col = "red", border = "black")
```




```
hist(DisJoint$meanA, main = "Histogram of DisJoint-Anthropomorphism ", xla
b = "means", ylab = "Frequency", col = "blue", border = "black")
```




```
hist(DisJoint$meanL, main = "Histogram of DisJoint-Like", xlab = "means",
ylab = "Frequency", col = "blue", border = "black")
```




```r
# Perform Shapiro-Wilk test
shapiro.test(Joint$meanA)

##
##  Shapiro-Wilk normality test
##
## data:  Joint$meanA
## W = 0.94704, p-value = 0.06534

shapiro.test(Joint$meanL)

##
##  Shapiro-Wilk normality test
##
## data:  Joint$meanL
## W = 0.95892, p-value = 0.1642

shapiro.test(DisJoint$meanA)

##
##  Shapiro-Wilk normality test
##
## data:  DisJoint$meanA
## W = 0.92529, p-value = 0.01273

shapiro.test(DisJoint$meanL)

##
##  Shapiro-Wilk normality test
##
## data:  DisJoint$meanL
## W = 0.90532, p-value = 0.003145
```

```
#wilcox test
wilcox.test(Joint$meanA, DisJoint$meanA, paired = TRUE, alternative = "gre
ater")

## Warning in wilcox.test.default(Joint$meanA, DisJoint$meanA, paired = TR
UE, :
## cannot compute exact p-value with ties

## Warning in wilcox.test.default(Joint$meanA, DisJoint$meanA, paired = TR
UE, :
## cannot compute exact p-value with zeroes

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  Joint$meanA and DisJoint$meanA
## V = 416, p-value = 0.1671
## alternative hypothesis: true location shift is greater than 0

wilcox.test(Joint$meanL, DisJoint$meanL, paired = TRUE, alternative = "gre
ater")

## Warning in wilcox.test.default(Joint$meanL, DisJoint$meanL, paired = TR
UE, :
## cannot compute exact p-value with ties

## Warning in wilcox.test.default(Joint$meanL, DisJoint$meanL, paired = TR
UE, :
## cannot compute exact p-value with zeroes

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  Joint$meanL and DisJoint$meanL
## V = 410, p-value = 0.1906
## alternative hypothesis: true location shift is greater than 0
```