The role of uncanny robot faces for attention and likeability in a gaze-leading study

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Abstract

Having one's gaze successfully followed has been found to be positive for social interactions, and robots who follow gaze have been found to be better liked than those who do not follow gaze. However, it is not yet known to what extent the effects of gaze leading differ between different face types. Therefore, a within-subjects comparison study was conducted using three face types: human faces, mechanical robots, and uncanny robots, and participants were asked to rank each face on likeability and anthropomorphism. In a motor response study, it was found that there was no difference in response time between different face types, nor between faces that typically followed gaze. Likeability and anthropomorphism were found to be higher in human faces compared to uncanny and robot faces. Additionally, robot faces that typically followed gaze were found to have a higher likeability, which correlates with previous studies. However, the results of the study indicate that using motor responses in long experiments on gaze leading might not be an ideal method as participants' behaviour might become automated after a certain point in time.

Introduction

Robots have the potential to support existing human labour in fields such as healthcare, with one example being to support the care of the elderly. However, much is still unknown about human-robot interaction. Thus, if we are to implement robots in healthcare or other fields with human contact, it is important to gather a deeper understanding of the social mechanisms of human-robot interaction to enable better communication and cooperation. Additionally, humanoid robots have been found to provide useful information about investigating social cognitive mechanisms in the human brain (Wykowska et al., 2016), meaning that research on the topic of human-robot interaction might give additional insights into our cognition. One feature of communication that applies to both interactions amongst humans and human-to-robot interaction is the role of gaze. In social interaction, the gaze can convey crucial information, such as one's mental state or interest in external objects or situations, which is the case in the phenomenon of gaze-leading, or, in other words, leading the gaze of another to an object or situation (Emery, 2000). Previous studies have used gaze-leading paradigms to investigate how joint attention is established and have found that people prefer others who follow their gaze (Bayliss et al., 2013, Willemse et al., 2018) and perceive others as more trustworthy when they follow one's gaze (Dalmaso et al., 2016). Specifically for robot design, understanding the importance of gaze following can enable robot designers to make robots that are more engaging to interact with by implementing specific eye gaze behaviours (Willemse & Wykowska, 2019). Making robots more engaging could, again, result in a more positive user experience, which is an essential part of choosing to adopt a technology (Hartson & Pyla, 2012).

The gaze-leading paradigm

With gaze playing a crucial role in communication (Emery, 2000), it is important to gather an understanding of the functions and the evolution of the human eye. The cooperative eye hypothesis, proposed by Tomasello et al. (2007), suggests that humans have evolved to have white sclera to enable better communication. By being able to identify a clear distinction between the iris and the sclera, it becomes easier to see what direction another person is looking, thus facilitating cooperation in social interactions. Additionally, gaze following has been documented to develop during infancy (Scaife & Bruner, 1975; Carpenter et al., 1998; Del Bianco et al., 2019) and has been found to be impaired in some people with autism or after localised brain lesions, suggesting that gaze following is hard-wired in the human brain (Emery, 2000; Langton et al., 2000). Thus, gaze following appears to be a behaviour that is inherent in humans.

Gaze following is typically coupled with the behaviour known as gaze leading. In contrast to gaze following, gaze leading can be described as when a person, the initiator, directs their attention to an object and another person, the follower, follows their gaze to attend to the same object (Emery, 2000). When both the initiator and the follower are attending to the same object, they are in a state called joint attention. A previous study found that when a person looks at an object and another individual follows their gaze to look at the same object, the person who was leading the gaze of the other will quickly orient their gaze to the individual who followed their gaze, indicating the existence of a social mechanism in humans to detect when one's gaze has been followed (Edwards et al., 2015). Furthermore, previous studies investigating the effects of gaze-leading have found that when person A (the initiator) is interacting with person B (the follower), person A will more quickly re-establish their attention to person B when person B shows gaze-congruent behaviour, or, in other words, typically follows person A's gaze (Bayliss et al., 2013).

Another study further investigated this effect with robots as the conversational agent and found that the effect of a quicker re-establishment of attention applies to robot faces that display gaze-congruent behaviour as well (Willemse et al., 2018). Furthermore, the study by Willemse et al. (2018) found that robots who follow your gaze are described as more pleasant and likeable, signifying that gaze following might be a significant element to include in robot design for robots meant for social interaction with humans.

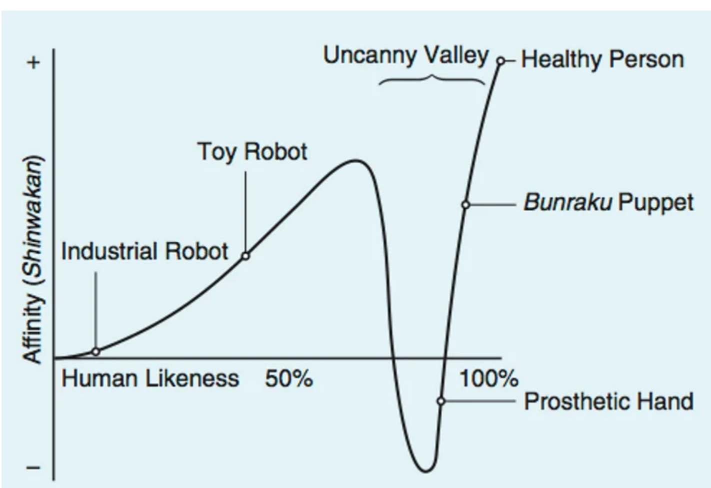
The two studies by Bayliss et al. (2013) and Willemse et al. (2018) show that gaze-leading has an effect on how humans interact with other agents, which applies to both human faces and robot faces. However, there have not been any studies using a within-subjects comparison of human and robot faces. Thus, what is left to question is the extent to which this effect differs between human faces and robot faces. For example, are the social mechanisms similar when interacting with a robot as compared to a human? Furthermore, the study by Willemse et al. (2018) only investigated one type of robot face, the iCub robot. As robots differ in design, it would also be of interest to investigate the extent to which the gaze-leading effect applies to different robot faces.

The Uncanny Valley

In robot design, one often discussed effect is the uncanny valley effect, as proposed by Mori et al. (2012). The uncanny valley effect describes the range in affinity towards an entity, where an increase in human likeness leads to increased affinity, until a certain point, named the valley, where affinity drops (see Fig. 1) (Mori et al., 2012). In other words, this valley describes the unpleasant feeling of looking at an entity that is close to human, but not exactly human. Although there are several suggestions on how the uncanny valley effect can be avoided in design, such as using stylisation, childish features, appealing features (Schwind et al., 2018) or dehumanising humanoid robots (Yam et al., 2021), there are still plenty of existing examples of both robots as virtual characters that fall into the uncanny valley (see for example Schwind et al. (2018) or Mathur et al. (2020)). The uncanny valley effect has been shown to affect how we perceive robots or avatars as social partners, with one example being how an uncanny valley effect in avatars (Shin et al., 2019) and robots (Mathur & Reichling, 2016) can negatively affect our trustworthiness towards them. Another example indicates that the decisions made by uncanny robots may be perceived as less moral than decisions made by humans or non-uncanny looking robots (Laakasuo et al., 2021). Therefore, it could be the case that an uncanny valley effect in a robot's face will lead to a less desirable social interaction compared to one that does not fall into the uncanny valley.

Figure 1

Graph depicting the Uncanny Valley



Note. The graph depicts the uncanny valley effect, where affinity increases the more human-like an entity becomes until it drops into the uncanny valley. Reprinted from The Uncanny Valley (p. 99) by M. Mori et al., 2012, *IEEE Robotics & Automation Magazine*, 19(2), 98-100.

It is still uncertain what exactly causes an entity to fall within the uncanny valley. Some studies link the eyes to an uncanny valley effect; humans with no eyes have been found to be perceived as uncanny (Schein & Gray, 2015), an eye-tracking study found that ambiguous faces lead to more perceptual processing of the eye and mouth area (Cheetham et al., 2013), and another study suggests that more credible eyes could lead to improved and less uncanny artificial figures (Schwind & Jäger, 2016). However, the uncanny valley effect has also been found to occur from the non-verbal behaviours of the entity, with one example being the role of gaze (Thepsoonthorn et al., 2021). Going back to the question about social mechanisms and gaze-leading, the aim is to investigate if there is a difference related to the gaze-leading effect between different types of robot faces, depending on where they fall in the uncanny valley.

Likeability and Anthropomorphism

In the study by Willemse et al. (2018), it was found that the robot faces that typically followed the gaze of the participants were perceived as more human-like and likeable than robots who did not typically follow the gaze. This finding indicates that humans might prefer other agents that follow their gaze compared to those who do not. In line with the current study, investigating the role of likeability and anthropomorphism, described as referring to "the attribution of a human form, human characteristics, or human behaviour to nonhuman things such as robots, computers, and animals" (Bartneck et al., 2009, p. 74), would allow us to see whether this effect persists for different types of faces. Furthermore, measures of likeability and anthropomorphism could give an indication as to how important gaze following is in a social situation compared to visual attributes, such as physical appearance. As previously mentioned, affinity is lower towards robots that are perceived to be uncanny (Mori, 2012). Thus, investigating measures on likeability and anthropomorphism could, for example, indicate whether a robot that falls into the uncanny valley and has a less desirable appearance but that does follow gaze would be perceived as more likeable than a robot with a more desirable appearance but that does not follow gaze.

Motor Responses to Study Gaze Following

In a study from 2022, Willemse et al. investigated whether the same effect of gaze-leading leading to a shorter time to re-direct one's attention to a face would be present for motor responses. Willemse et al. theorised that motor responses might reveal similar findings to eye-tracking studies, as there are several overlapping factors between gaze and motor responses. One such example is pointing, which is used by many to direct another person's attention to an object or situation (Bangerter, 2004). Moreover, there has been found to be an overlap between the regions of the brain that are central to hand movements and eye movements (Leung & Cai, 2017). By conducting the same experiment as the two studies by Willemse et al. (2018) and Willemse and Wykowska (2019) but with participants using a mouse to click on their preferred objects and the faces in place of eye-tracking, Willemse et al. (2022) found that participants still interacted more quickly with robot faces that followed their "gaze" or click. This finding indicates that there might be similar attentional mechanisms behind hand movements and eye movements and suggests that conducting an experiment using mouse clicking in place of eye tracking is a viable method.

If motor responses prove to be a viable method, using motor responses in place of eye tracking could be a cost-effective method to study gaze leading. Additionally, it could be possible to reach more participants in studies as a study using only a mouse and a computer screen could be administered digitally, without the need for a researcher to supervise the participant. Furthermore, a motor response experiment is arguably simpler to both set up and to create than an experiment requiring an eye tracker, making it an approach that is quicker and easier to replicate than a study using eye tracking equipment.

Aim of the Study

The present study builds upon the previous studies by Willemse et al. (2018), Willemse and Wykowska (2019), and Willemse et al. (2022). In these three past studies, the main topic of interest has been to investigate gaze-leading by conducting an experiment where participants "lead" the gaze of a robot face presented on a computer screen by choosing one of two objects presented and looking at the chosen object. The robot face would then either follow the gaze of the participant or look at the other object.

Based on previous studies and literature, the present study aims to fill in several gaps in knowledge to further investigate the gaze-leading paradigm and its effects. The first aim of the study is to explore any differences in the response time of re-establishing attention on a face for different face types. By comparing three different face types, being human, mechanical robots, and uncanny robots in both joint and disjoint conditions it will be possible to determine if different types of faces influence how quickly participants re-establish attention. As previous literature has indicated that people are quicker to reorient their attention to faces that follow their gaze, the present study can give an indication of whether this effect will remain the same for different face types or if it will differ based on which face is presented. Knowing the importance of gaze for different types of faces could help in the design process of robots to make robots that ensure a better user experience.

Additionally, the study aims to give an insight into whether there is a difference in likeability and anthropomorphism for the different face types in the different dispositions (joint/disjoint). As previous research indicates that robot faces that are in the joint disposition are found to be preferred, investigating measures on anthropomorphism and likeability for different face types can give an indication as to how important gaze following is compared to physical appearance.

Lastly, the study aims to give further insights into using motor responses to conduct a gaze-leading experiment by conducting a study using a mouse as a means to direct gaze. As mentioned, motor responses could be a cost-effective and easier alternative to eye tracking. However, it is still essential to determine whether using motor responses is a viable method compared to eye-tracking.

Methods

Participants

A total of 36 participants took part in the study. However, the data of one participant was discarded as only half of the data from the experiment was recorded due to the program crashing halfway through the experiment. Thus, the data analysis is based on the data of the remaining 35 participants (15 females, 20 males, Age $M = 24.86$, $SD = 10.56$, 32 right-handed and 3 left-handed). The participants were recruited via convenience sampling and through the SONA system where participants could sign up in exchange for credit as compensation for the completion of the study. The study was granted ethical approval by the BMS Ethics Committee (request number 231383).

Materials

Stimuli

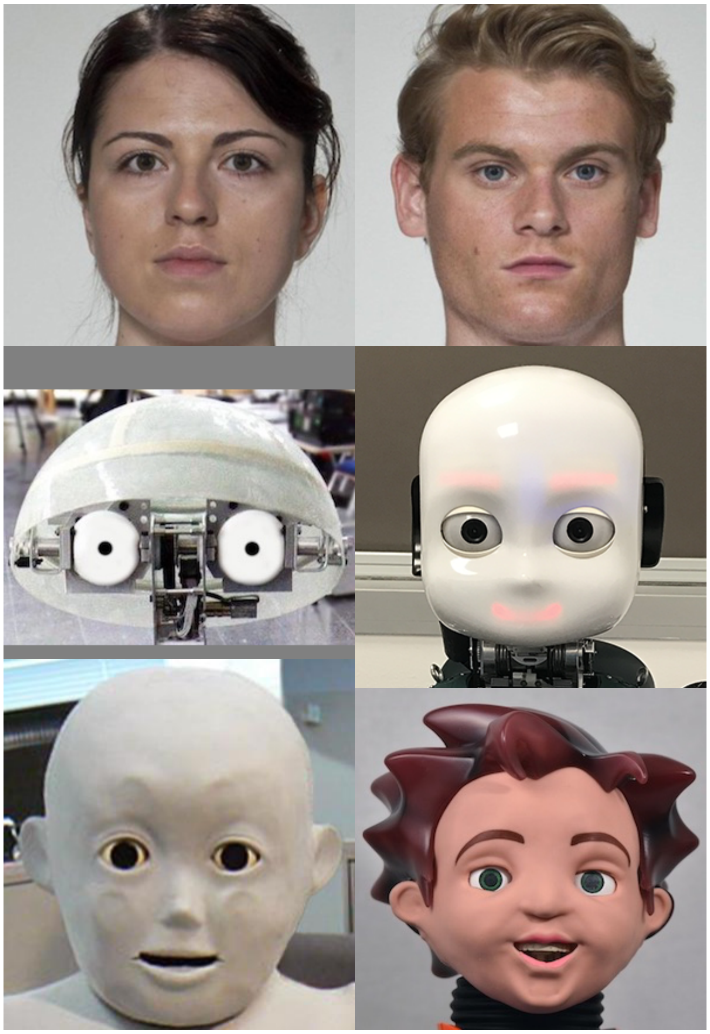
The experiment included six stimuli; two human faces, two mechanical robot faces, and two uncanny robot faces (see Fig. 2). The human faces were sourced from the London repository, which includes human faces of various ages and ethnicities (DeBruine & Jones, 2017). The repository includes a supplement that includes the ratings of attractiveness for each face based on a sample of participants. Two human faces, one male and one female, were chosen at random from the repository. The chosen faces had to (1) be looking straight at the camera with no tilting of the head in any direction, (2) have a clear distinction between sclera and iris/pupil (i.e. no dark shadows on the sclera with a similar shade of the iris) to make it possible to edit the eyes in the picture in a way that participants would be able to tell that the face is looking in a certain direction, and (3) score similarly on the attractiveness rating. For the two chosen faces, both the male and the female face scored a three out of seven on the attractiveness rating.

The robot faces were chosen based on a study on the uncanny valley by Mathur et al. (2020). The study includes a selection of human- and robot faces, ranging from mechanical to uncanny to human. Two faces on the mechanical side of the spectrum were chosen to represent the two mechanical robot faces and two faces ranging close to the deep point of the uncanny valley were chosen to represent the uncanny robot faces. These faces had to satisfy the same criteria as the human faces, meaning that a large section of the robot faces was excluded as there was not a clear enough distinction between sclera and iris/pupil in many of the photos.

The six faces that were chosen as stimuli were edited in the free image-editing software GIMP (version 2.10.36, available at www.gimp.org) by changing the placement of the iris and pupil to give the appearance of the face looking either to the left or the right. Each face was edited to have three different states: (1) looking straight ahead, (2) looking to the right, and (3) looking to the left. The objects the participants could choose from in the object-picking task were adapted from Willemse et al. (2018).

Figure 2

Stimuli used in the experiment



Note. The top two faces are in the “human” face type, the middle two are in the “robot” face type, and the bottom two are in the “uncanny” face type. The three faces in the left column were following the gaze of the participants 80 percent of the time for participants in List 1, and not following 80 percent of the time for participants in List 2. This was reversed for the faces in the right column.

Figure 3

Example screens of the experiment that were shown to participants

Note. The top image illustrates one of the six faces (in this case, the face "Uncanny 2") with two objects on either side. After clicking the object on the right, the face in the middle looks at the object on the left (bottom image).

Program and Questionnaire

The object-picking task entailed participants choosing their preferred object between two objects, with one object located at each side of a face in the middle of the monitor (see Fig. 3). After clicking on the preferred object, the face would shift its gaze to either the same object (following the "gaze" of the participant's click) or the other object (not following the gaze). The object-picking task was programmed in PsychoPy version 2023.2.3 (Peirce et al., 2019).

In addition to the task, participants were presented with a questionnaire. This questionnaire included a consent form, three demographic questions regarding participants' gender, age, and whether they were right or left-handed, and the items of the anthropomorphism and likeability factors of the Godspeed questionnaire (Bartneck et al., 2009). The Godspeed questionnaire is intended to measure people's perception of robots and includes five factors; anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety (Bartneck et al., 2009). However, for the present research, only the factors of anthropomorphism and likeability were considered relevant, hence the remaining three factors were not included. The Godspeed questionnaire includes five pairs of two bipolar words (e.g. fake - natural, unfriendly - friendly) for each of the five factors (Bartneck et al., 2009). Each set of words is ranked on a semantic differential scale from one to five.

It should be noted there is some debate as to whether the Godspeed questionnaire is suitable for evaluating people's perception of robots. Notably, Ho and MacDorman (2010) found that the measures of anthropomorphism, likeability, animacy, and perceived intelligence were found to be highly correlated, which could indicate that they are measuring the same concept. However, attempting to measure people's emotional response to entities falling into the uncanny valley using a questionnaire will result in items that are rated subjectively, meaning that a questionnaire will likely never be a perfect method of capturing this response. In this light, the Godspeed questionnaire was considered to be appropriate for the present study, as it would allow a comparison with the previous study by Willemse et al. (2018), which also made use of the Godspeed questionnaire.

The questionnaire also included items from the AQ-10, or the Autism Spectrum Quotient, a questionnaire designed to indicate whether a person might be situated on the autism spectrum (Allison et al., 2012), and the MASC, a video meant to assess social cognition (Dziobek et al., 2006). However, these metrics were included in a different study and are thus not relevant to the present study.

Procedure

After being recruited, participants showed up either at a lab space with a monitor set up or at the home of one of the researchers. Participants were seated in front of a monitor or a laptop screen when the experiment took place at the home of a researcher. In both cases, an external mouse (not a trackpad) was used. Participants were first instructed to read a consent form and give their consent to participate before they could proceed with the study. Then, three questions regarding demographics (age, gender, and whether they were left or right-handed) were answered. After filling in their answers, participants were directed to the experiment in PsychoPy. Each participant was assigned to either list one or list two.

Participants were first given written instructions with a figure to show how the experiment worked. The researcher gave further oral instructions to the participant if needed. After being instructed, participants completed a practice run with eight trials (face and object combinations). After completing the practice run, participants were instructed that the experiment would start. The experiment proceeded as follows: A fixation cross appeared in the middle of the screen for 500 ms. Then, the first set of stimuli appeared (see Fig. 3 for an example), including one of the six faces and a set of objects (one object on either side of the face). The participants then had to choose their preferred object and click on it. After clicking the object, the face in the middle would look towards either the same object the participant chose (following gaze) or the other object (not following gaze). After the face directed its gaze to one of the objects, the participant clicked on the face. This procedure was then repeated. There were in total eight blocks of 60 trials, with the possibility to take a break in between each block. The faces and objects appeared in random order with a set number of appearances, with each of the six faces appearing a total of 60 times over the course of the entire experiment. For each trial, six faces (two humans, two mechanical robots, and two uncanny robots) would appear in random order with a random combination of a set of objects. For participants in List 1, one face of each face type would look towards the chosen object eighty percent of the time (joint condition) whereas the remaining three faces would look towards the non-chosen object eighty percent of the time (disjoint condition). For list two, this was reversed (i.e. the faces that were in the joint condition for list one was in the disjoint condition for list two with the same applying to the disjoint condition).

After completing all eight blocks of the experiment, participants were redirected to the questionnaire. First, they were instructed to fill in the Godspeed questionnaire. For each of the six faces, participants were asked to rank in total ten sets of bipolar words on a scale from one to five. After completing the Godspeed questionnaire, participants were instructed to fill in the AQ-10 and the MASC. For the MASC, one video clip was shown before they answered each question, with five video clips and five questions in total.

After completing the questionnaire, participants were thanked for their participation and credit was given to any participants recruited through the SONA system.

Data Processing

All data was analysed in R (version 2023.03.0), using the packages Tidyverse (Wickham et al., 2019), lme4 (Douglas Bates et al., 2014), and ggeffects (Lüdecke, 2018). The data from PsychoPy was first cleaned and only relevant data (*Participant number, List, Following* (if face followed or did not follow gaze), *RT* (time from clicking on object to clicking on face), and *Face* (indicated which face type appeared in each trial)) was imported to a dataset. Two additional columns, *Disposition* (whether the face was in the joint or disjoint condition) and *Facetype* (whether the face was human, robot, or uncanny) were added. The response times were converted to milliseconds for convenience. Any response times lower than 100 ms or higher than 2000 ms were discarded to clear out any outliers as these were not deemed relevant to the results. A response time higher than 2000 ms would likely be too long for the direction of the gaze of the face on the screen to have any impact on the response time as a response that long would likely be biased by conscious thought. Similarly, a response time lower than 100 ms would likely be too quick for there to be an impact of the gaze direction as the fastest possible reaction time to a stimulus is about 100 ms (Baars & Gage, 2010). The data from Qualtrics (anthropomorphism and likeability scores, as well as demographic data) was then added and merged with the PsychoPy data.

The average response times (i.e. the time passed from clicking on the object to clicking on the face) were calculated, both overall and per list. Furthermore, the average response times for the first half and the second half of the experiment were calculated to be able to compare how the response time evolved over the course of the experiment. Additionally, means were calculated for the anthropomorphism and likeability scores per face and list.

A linear mixed effects model was used to analyse the data. For the linear mixed model, response time was set as the dependent variable, with disposition, face type, and following behaviour as conditional effects on response time and participant as a random effect. The data included two types of dispositions (joint/disjoint), two following behaviours (followed / unfollowed), and three face types (human/robot/uncanny). An overview of the effects and an explanation of each effect can be seen in Table 1.

Additionally, the dataset included the variables Anthropomorphism and Likeability. In line with the research question, it was of interest to determine if these two variables would be influenced by disposition or face type. To determine if that was the case, two additional linear mixed effect models were applied with either Anthropomorphism or Likeability as the dependent variable, with the variables Disposition and Face Type as conditional effects on either anthropomorphism or likeability and Participant as a random effect.

Table 1

Explanation of Parameters in Linear Mixed Model

Parameter name	Explanation
Following unfollowed	The effect of following behaviour on response time for the human face type
Disposition disjoint	The effect of disposition on response time for the human face type
Facetype robot	Whether a face in the robot face type results in a different response time
Facetype uncanny	Whether a face in the uncanny face type results in a different response time
Following unfollowed: disposition disjoint	The effect of following behaviour on response time for the human face type in the disjoint disposition
Following unfollowed: facetype: robot	The effect of following behaviour on response time for the robot face type
Following unfollowed: Facetype uncanny	The effect of following behaviour on response time for the uncanny face type
Disposition disjoint: facetype robot	The effect of disposition for the robot face type on response time
Disposition disjoint: facetype uncanny	The effect of disposition for the uncanny face type on response time
Following unfollowed: disposition disjoint: facetype robot	The effect of following behaviour on response time for the robot face type in the disjoint disposition
Following unfollowed: disposition disjoint: facetype uncanny	The effect of following behaviour on response time for the uncanny face type in the disjoint disposition

Results

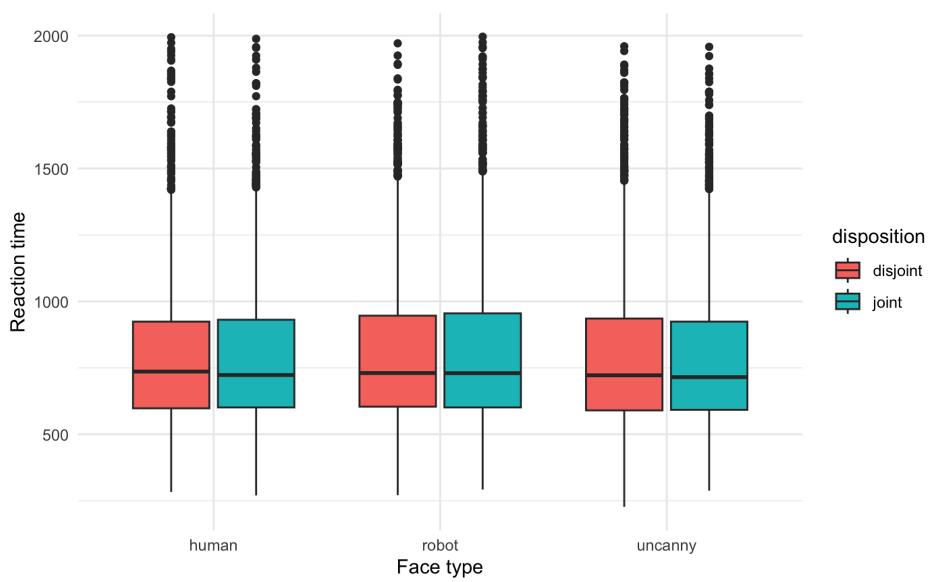
Response Times

Average Response Times

A visual representation of the average response times per face type and disposition can be seen in Fig. 4. There was not found to be a large difference between the average response time in the joint and disjoint disposition for all face types. For both the human and uncanny face types, the difference between the average response time for the joint disposition and the disjoint disposition was 4 ms, and for the robot face type, this difference was only 1 ms. Furthermore, there does not appear to be a difference in average response time between the three face types.

Figure 4

Average response time for each face type and disposition

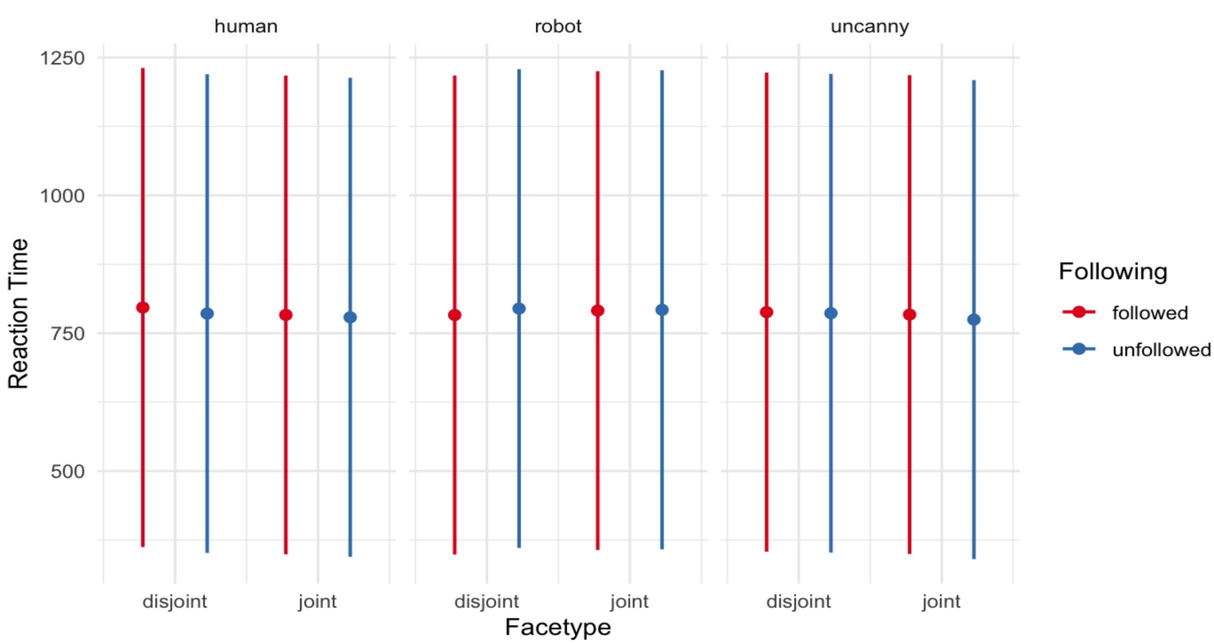


Linear Mixed Model of Response Time, Face Type, Disposition, and Following Behaviour

A linear mixed model was used to analyse the data. The data included three face types, two types of dispositions, two types of following behaviour, and a response time of 480 trials per participant, with a total of 35 participants. The fixed effects of the linear mixed effects model of response Time, with Face Type, Disposition, and Following behaviour as conditional effects can be seen in Table 2, and a visual representation can be seen in Figure 5.

Figure 5

Plot of Fixed Effects of Response Time, Face Type, Following behaviour, and Disposition



Note. The figure displays the response time for each of the three face types (human, robot, and uncanny) in both joint and disjoint conditions, and for both following behaviours (following and unfollowed).

The random effect of “participant” had a standard deviation of 162.3, which indicates that there is a high degree of variance in response time between participants. In Table 2, it can be seen that the unfollowed behaviour (parameter name Following unfollowed) has an estimate of only -4.4 ms, with confidence intervals that are several magnitudes larger. In prior gaze-leading studies, effects have been found at around 20 ms, but that is still a considerably higher number than what was found for the “Following unfollowed” parameter. Therefore, it is possible to determine that no effect of the following behaviour on response time for the human face type was found.

The parameter “Disposition disjoint” was found to have an estimate of 13.4 ms, which is still too low to have an effect on response time. Similarly, the confidence intervals show high uncertainty as they are several times higher than the estimate. Thus, no difference was found between joint and disjoint disposition for the human face type.

The parameter “Facetype robot” had an estimate of 7.8 ms with confidence intervals around four times larger than the estimate. Again, the estimate is too low to indicate an effect and there is high uncertainty for the estimate. Therefore, there was not found to be a difference in response time between the robot face type and the human face type. Similarly, the uncanny face type did not reveal a difference in response time compared to the human face type, with an estimate of only 0.7 ms and confidence intervals that are several magnitudes higher.

The parameter “Following unfollowed: disposition disjoint” indicates that there was no effect on response time of following behaviour when taking disposition into account for the human face type. Similar to previously mentioned parameters, the effect was found to be very small with an estimate of only -6.6 ms and confidence intervals that were much larger than the effect.

Table 2

Fixed effects of LMM for Response Time, Face Type, Disposition, and Following Behaviour

Parameter name	Estimate	Standard error	Lower 2.5%	Upper 97.5%
(Intercept)	783.14	27.85	727.87	838.39
Following unfollowed	-4.35	10.84	-25.59	16.89
Disposition disjoint	13.42	10.98	-8.09	34.93
Facetype robot	7.84	6.88	-5.63	21.31
Facetype uncanny	0.67	6.89	-12.83	14.16
Following unfollowed: disposition disjoint	-6.61	15.43	-36.85	23.63
Following unfollowed: facetype: robot	5.79	15.39	-24.37	35.94
Following unfollowed: Facetype uncanny	-4.83	15.38	-34.97	25.31
Disposition disjoint: facetype robot	-21.44	15.47	-51.75	8.87
Disposition disjoint: facetype uncanny	-9.01	15.41	-39.20	21.18
Following unfollowed: disposition disjoint: facetype robot	16.91	21.83	-25.85	59.69
Following unfollowed: disposition disjoint: facetype uncanny	13.81	21.77	-28.85	56.47

The parameter "Following unfollowed: facetype robot" indicates that there was no effect found of following behaviour for the robot face type on response time, with, again, a very small estimate of only 5.8 ms and confidence intervals that are magnitudes larger. Similarly, the parameter “Following unfollowed: facetype uncanny” reveals no difference in response time for the following behaviour for the uncanny face type with a small estimate of -4.8 and wide confidence intervals.

The parameter “Disposition disjoint: facetype robot” was found to have a somewhat high effect of -21.4 ms, which is an estimate that is similar to what has been seen in other gaze-leading studies. However, the confidence intervals indicate very high uncertainty as the range is around three times larger than the estimate, meaning it is unlikely that disposition in the robot face type has an effect on response time. As for the disposition for the uncanny face type, the parameter “Disposition disjoint: facetype uncanny” has a smaller effect of -9.0 ms and wide confidence intervals, meaning there was not found to be an effect of disposition on response time for uncanny faces.

When taking both following behaviour and disposition into account for the robot face type, the parameter “Following unfollowed: disposition disjoint: facetype robot” was found to have one of the higher estimates with 16.9 ms. However, this estimate is still lower than what has been found in previous gaze-leading studies, and, combined with high uncertainty with confidence intervals that are several times larger than the effect, there is no indication of there being any difference in response time when taking both following behaviour and disposition into account for the robot face type.

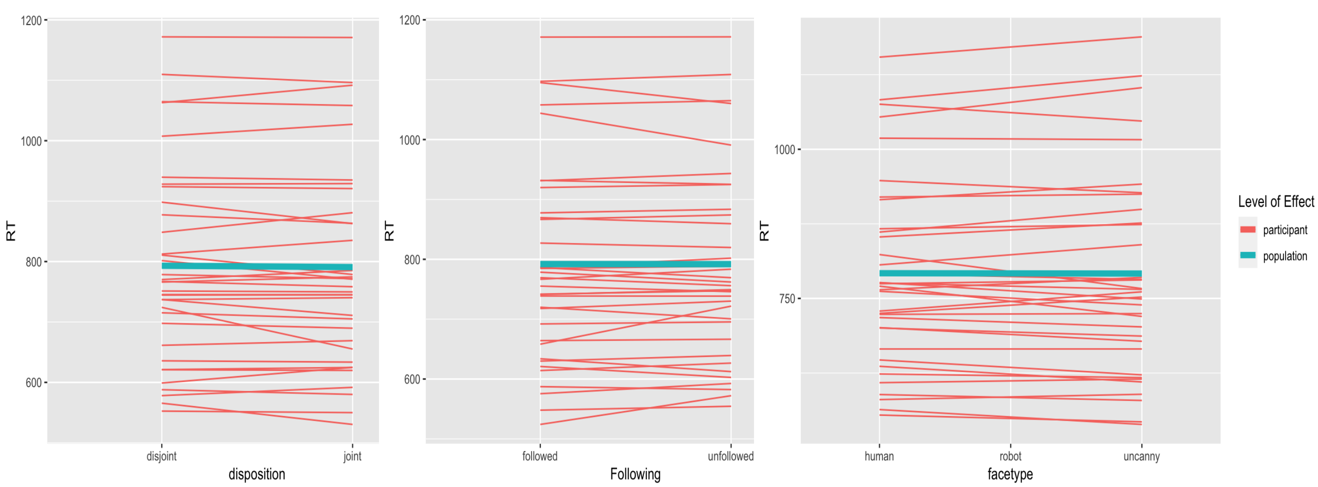
For the uncanny face type, the parameter “Following unfollowed: disposition disjoint: facetype uncanny” reveals no effect on response time with an estimate of 13.8 ms and confidence intervals that are several times larger than the estimate. Thus, when taking both the following behaviour and disposition into account for the uncanny face type, there does not appear to be any effect on response time.

Universality

As no effect was found for any of the parameters on response time, it was of interest to determine whether this lack of effect was the case for every participant, or whether there were some participants where differences in response time could be distinguished for the various parameters. Therefore, a graphical universality analysis was done (see Fig. 6). As can be seen in the three spaghetti plots, there do appear to be a few participants that have a different response time for either disposition, following behaviour, or face type, but the majority of the participants do not appear to have a different response time. As there are so few participants that show a difference in response time, it is unlikely that only a certain group of participants respond to the effects of gaze leading.

Figure 6

Spaghetti plots of differences in response time for each participant for Disposition, Following Behaviour and Face Type



Note. The leftmost plot shows the differences in response time for each participant for both dispositions, the middle plot shows the differences in response time for both following behaviours, and the rightmost plot shows the differences in response time for the three face types.

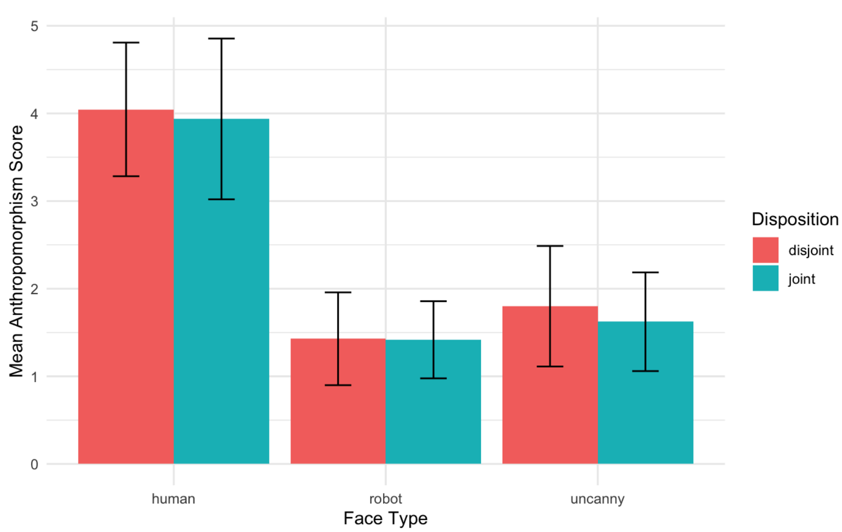
Anthropomorphism

Average Anthropomorphism Scores

The average scores for anthropomorphism, rated on a 5-point scale, were found to be higher in the disjoint condition than in the joint condition for all the face types (see Fig. 7). The largest difference between the two dispositions within a face type was seen for the uncanny face type, with a difference of 0.19 between the joint and disjoint dispositions, with the disjoint disposition having the higher average score. However, this difference is still relatively small, as can be observed in Figure 7. For the robot face type, the difference between the joint and disjoint condition was considerably smaller, with a difference of only 0.03 between the joint and disjoint dispositions, and from Figure 7 it becomes clear that there is almost no difference between these values. Without taking disposition into consideration, human faces were found to have the highest mean score for anthropomorphism (M = 4.01), followed by uncanny faces (M = 1.74), and robot faces with the lowest mean score (M = 1.44).

Figure 7

Mean Anthropomorphism score per face type and disposition



Linear Mixed Model for Anthropomorphism, Face Type, and Disposition

The second linear model included the data of three face types, two dispositions, and the participant scores for anthropomorphism for each face, thus resulting in six anthropomorphism scores per participant. Anthropomorphism was rated on a scale of one to five. The fixed effects of the second linear mixed model, with anthropomorphism as the dependent variable, and Face type and Disposition as conditional effects on anthropomorphism, can be seen in Table 3, with a graphical representation in Figure 8. The random effect “participant” had a standard deviation of 0.38, indicating that there is not a very high level of variance in anthropomorphism scores between participants.

The linear mixed model revealed that the robot- and uncanny face types were found to have a lower Anthropomorphism compared to human faces, as can be seen in Table 3. The robot face type had the lowest anthropomorphism score with an estimate of -2.62, with narrow confidence intervals indicating a high certainty. This indicates that robot faces are perceived to have an anthropomorphism score that is almost three times lower than that of human faces. Similarly, there is a high certainty that the uncanny face type has a lower anthropomorphism score compared to human faces with an estimate of -2.25 with narrow confidence intervals. Thus, the uncanny face type was found to have a slightly higher anthropomorphism score compared to robot faces, but both robot and uncanny faces had a much lower score than human faces.

Additionally, the analysis indicated a high certainty of a somewhat lower Anthropomorphism for human faces in the joint condition compared to the disjoint condition. However, the estimate was found to be only -0.10 with the score being on a rating scale of one to five, indicating that this effect is very weak. Robot faces in the joint condition compared to the disjoint condition were found to have a slightly higher anthropomorphism with an estimate of 0.09.

However, similar to the human face type, this effect is very weak, and the lower bound of the confidence interval reveals that the effect might be close to zero. Furthermore, in Figure 8, it is difficult to distinguish any difference between the disjoint and joint conditions for the robot faces, further indicating the weakness of the effect. Uncanny faces in the joint condition compared to the disjoint condition were found to have a slightly lower Anthropomorphism with an estimate of -0.08. However, this effect is, again, on the weaker side with the higher bound of the confidence interval indicating the effect might be close to zero.

Thus, there seems to be little indication of anthropomorphism differing between the joint and disjoint disposition for any of the face types. For all three face types, the difference between the joint and disjoint disposition was found to be around 0.1, and considering anthropomorphism was ranked on a 5-point scale, the effect is not strong.

Figure 8

Plot of Fixed Effects Estimates for Anthropomorphism

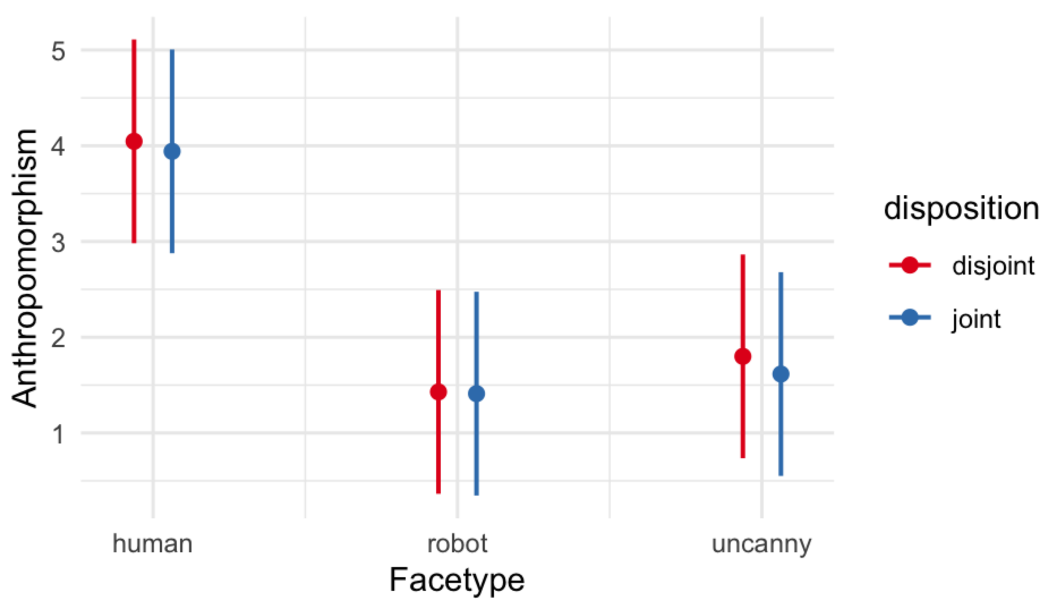


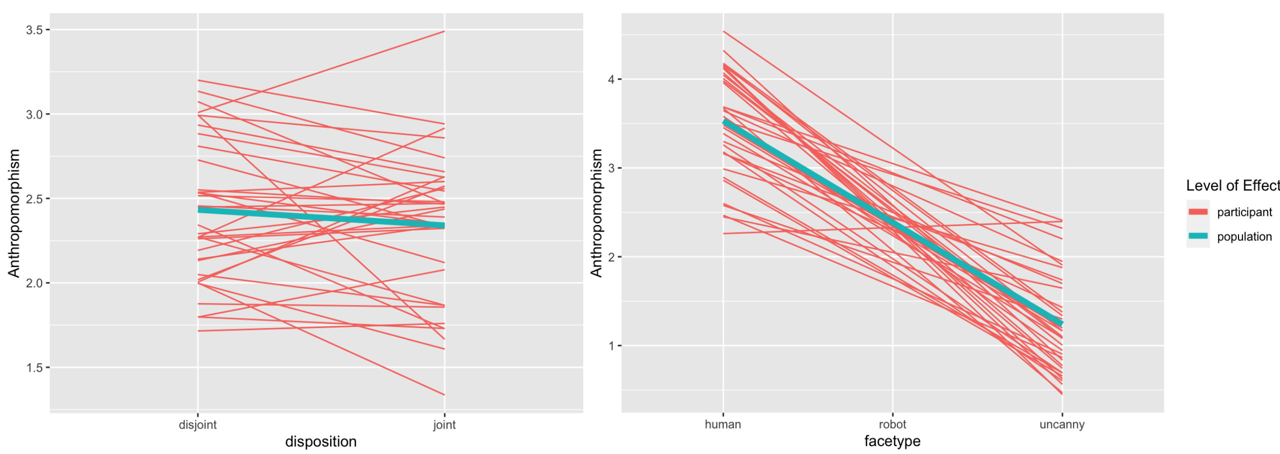
Table 3

Fixed Effects of Linear Mixed Model of Anthropomorphism

Parameter name	Estimate	Standard error	Lower boundary 2.5%	Upper boundary 97.5%
(Intercept)	4.05	0.07	3.92	4.18
Facetype robot	-2.62	0.02	-2.65	-2.59
Facetype uncanny	-2.25	0.02	-2.28	-2.25
Disposition joint	-0.10	0.02	-0.13	-0.08
Facetype robot: disposition joint	0.09	0.02	0.04	0.13
Facetype uncanny: disposition joint	-0.08	0.02	-0.12	-0.04

Figure 9

Spaghetti plots of differences in anthropomorphism for each participant for Disposition and Face Type



Note. The plot on the left shows the difference in anthropomorphism scores between the joint and disjoint dispositions for each participant, and the plot on the right shows the differences in anthropomorphism for the three face types.

To determine if there were any notable differences in anthropomorphism scores between participants for disposition and face type, a graphical universality analysis was done. In the two plots that can be seen in Figure 9, it is possible to remark that anthropomorphism scores appear to be slightly lower in the joint disposition for a large group of participants, but there is an approximately equal-sized group of participants where the disjoint disposition have the lower anthropomorphism score. Thus, there does not appear to be a majority that has a higher score for either disposition. As for the face type, it is clear that most participants indicate a higher anthropomorphism score for the human face type, which aligns with the findings of the linear mixed model and mean scores.

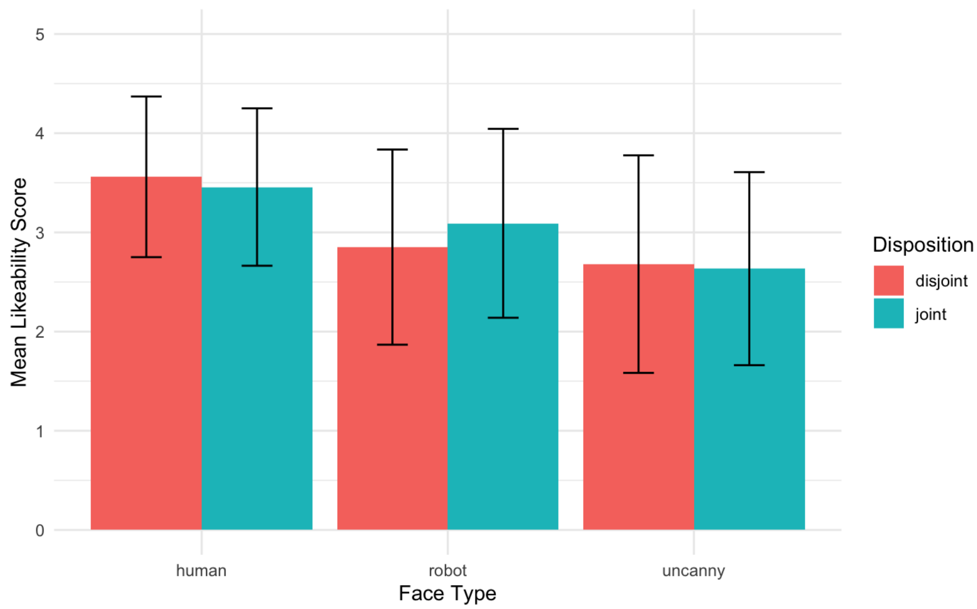
Likeability

Average Likeability Scores

The average likeability scores ranked on a 5-point scale, can be seen in Figure 10. Likeability had an average score that was slightly higher in the disjoint condition for the human face type compared to the joint disposition, with a difference of 0.08. Similarly, the uncanny face type had a higher average in the disjoint disposition compared to the joint condition with a slightly higher difference of 1.5 between the two dispositions. For the robot face type, likeability was found to be higher for the joint disposition compared to the disjoint disposition with a difference of 0.21. When disregarding disposition, the human face type was found to be the most likeable with a mean score of 3.53, followed by the robot face type (M = 2.98), and the uncanny face type with the lowest average likeability (M = 2.68).

Figure 10

Mean Likeability score per face type and disposition



Linear Mixed Model for Likeability, Face Type, and Disposition

The third linear model included the data of three face types, two dispositions, and the participant scores for Likeability for each face for a total of six likeability scores per participant. Likeability was ranked on a scale of one to five. The fixed effects of the third linear mixed model, with Likeability as the dependent variable, and Face type and Disposition as conditional effects on likeability, can be seen in Table 4, with a graphical representation in Figure 11. The random effect of "participant" was found to have a standard deviation of 0.47, indicating that there is a moderate amount of variance in likeability scores between participants.

Figure 11

Plot of Fixed Effects Estimates for Likeability

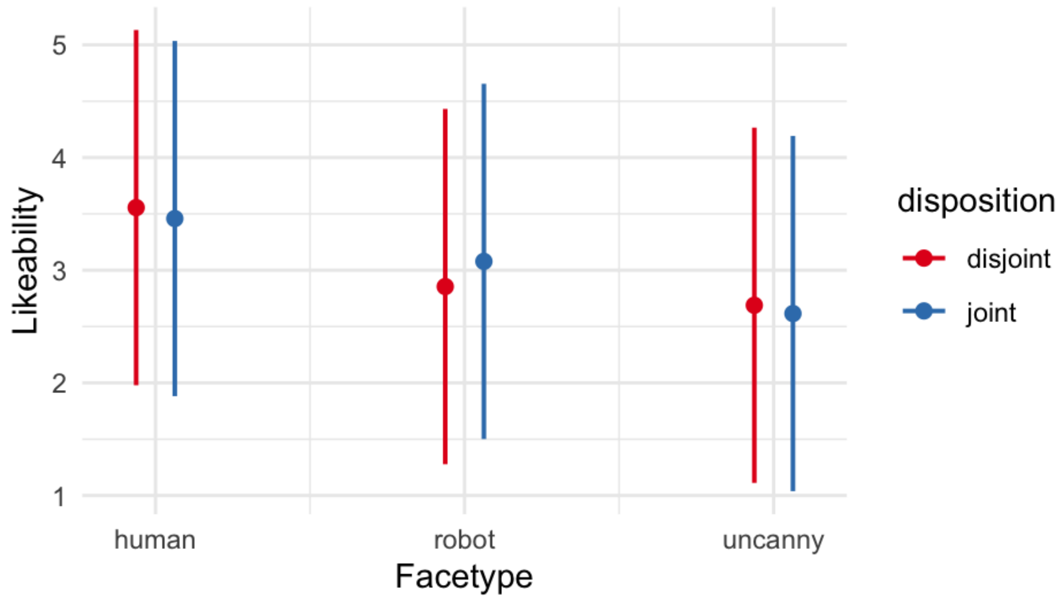


Table 4

Fixed Effects of Linear Mixed Model of Likeability

Parameter name	Estimate	Standard error	Lower boundary 2.5%	Upper boundary 97.5%
(Intercept)	3,56	0,08	3,40	3,72
Facetype robot	-0,70	0,02	-0,74	-0,66
Facetype uncanny	-0,87	0,02	-0,91	-0,82
Disposition joint	-0,10	0,02	-0,14	-0,05
Facetype robot: disposition joint	0,32	0,03	0,26	0,38
Facetype uncanny: disposition joint	0,02	0,03	-0,04	0,09

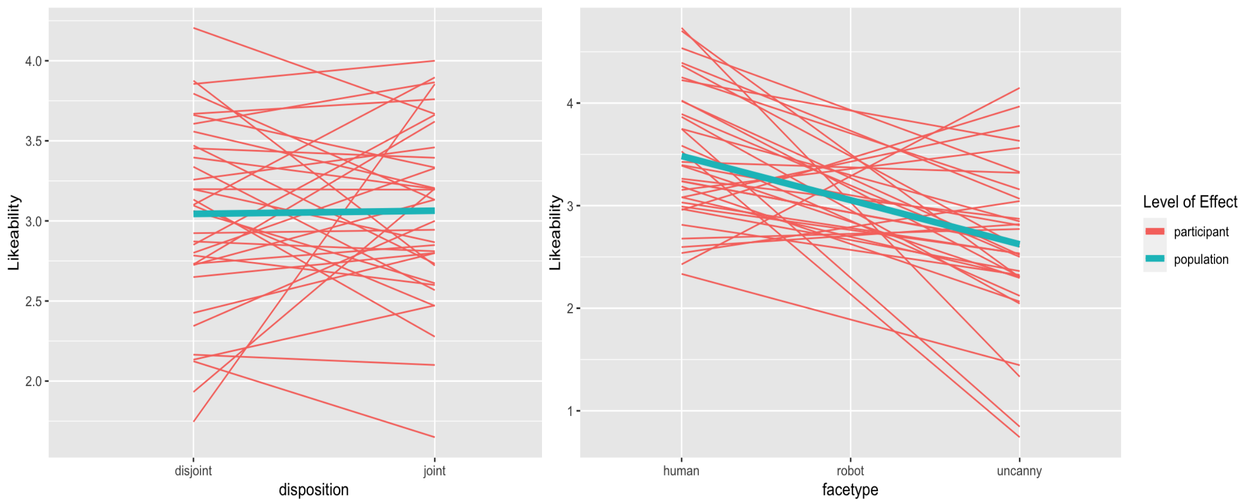
As can be seen in Table 4, likeability was found to have a high certainty of being lower for the robot and uncanny face types compared to human faces, with the estimate for robot faces being -0.70 and uncanny faces with an estimate of -0.87. These findings indicate that uncanny faces have the lowest likeability out of the three face types, which can be observed in Figure 9.

Disposition seems to have a small effect on the likeability of human faces, with the joint disposition having an estimate of -0.10, which indicates that likeability is lower in the joint disposition compared to the disjoint disposition for human faces. However, taking the upper limit of the confidence interval of -0.05 into account, the effect is very small and might be close to zero. For robot faces, likeability has a high certainty of being higher in the joint disposition compared to the disjoint disposition, with a relatively strong estimate of 0.32. Furthermore, there is a visible difference in likeability between the joint and disjoint disposition for the robot face type in Figure 9, further indicating that this effect is stronger. As for the uncanny face type, there was not found to be a difference between the disjoint and joint disposition. With an estimate of only 0.02 and a standard error of 0.03, it is possible to say that there is little to no effect. Thus, it appears that the only face type where there is a notable difference in likeability between the joint and disjoint disposition is the robot face type.

A graphical universality analysis was done to determine if there were any differences in likeability scores between the two dispositions and the three face types for each participant. As can be seen in the plots in Figure 12, there appears to be around an equal number of participants that indicate a higher likeability score for both dispositions, resulting in a population average around zero. As for the face type, the majority of participants appear to have a higher likeability score for human faces, although there are a handful of participants that indicate a lower likeability for the human face type. However, there does appear to be a pattern similar to what was observed from the mean likeability scores and the linear mixed model, namely that the human face type has the highest likeability.

Figure 12

Spaghetti plots of differences in likeability for each participant for Disposition and Face Type



Note. The plot on the left shows the difference in likeability scores between the joint and disjoint dispositions for each participant, and the plot on the right shows the differences in likeability for the three face types.

Discussion

To design robots that are preferable to interact with and make the user experience of interacting with robots better, the present study aimed to investigate the importance of gaze in human-robot interaction. In the present study, a within-subjects gaze-leading study using motor responses and three different face types was conducted, with the aim to determine whether different face types would result in a different response time to re-establish attention on a face. Additionally, the study aimed to investigate whether there would be a difference in anthropomorphism and likeability for different face types in the joint disposition compared to the disjoint disposition. From previous studies, it was expected to see a higher likeability and a shorter response time for faces with a joint disposition, meaning faces that typically follow one's gaze.

Response Time to Re-establish Attention on the Face

The present study aimed to investigate whether there was a difference in the time it took participants to click on faces following their gaze (joint condition), compared to faces that did not follow their gaze (disjoint condition). Furthermore, the study aimed to determine whether there was a difference in the time of these return clicks for the human, robot, and uncanny face types. Contrary to what previous studies have found (Bayliss et al., 2013; Willemse et al., 2018; Willemse & Wykowska, 2019; Willemse et al., 2022), the results of the present study did not find there to be any difference in the time of the return clicks between the joint and disjoint condition, meaning that participants did not re-establish their attention quicker to faces that followed their gaze. Moreover, there was also no difference in the time of return clicks for the different face types, meaning that participants do not appear to re-establish their attention quicker to any one type of face (human, robot, or uncanny).

Motor Responses

The present study was further aimed at determining whether using motor responses in a gaze-leading study is a viable method. The study by Willemse et al. (2022) conducted an experiment with motor responses and found that it seemed to be a viable method, but it should be noted that the experiment was notably shorter than the experiment in the present study. In the current study, it was noticed by the researchers that participants tended to speed up considerably the further along they went in the experiment and the clicking behaviour seemed to become more rhythmic. When comparing the average response times of the first half of the experiment (843 ms) to the second half (742 ms), the average response time is considerably shorter in the second half of the experiment, dropping by approximately 100 ms[1]. Similarly, the standard deviation is lower in the second half with a value of 248 ms, compared to 287 ms in the first half. This indicates that the response times are less varied in the second half compared to the response times in the first half, which could be an indication of the response clicks becoming more uniform or rhythmic, as noted by the researchers.

Human behaviour is a mixture of conscious and automatic efforts (Bargh & Chartrand, 1999), and McBride et al. (2012) found that visual stimuli cause automatic motor activation that occurs without conscious effort. During easy motor tasks, such as the experiment in the present study, automation of behaviour can allow for tasks to be completed more quickly with little conscious effort. Therefore, it is possible that the clicking behaviour of participants became automated at a certain point, at which participants might no longer have been influenced by the direction of the gaze of the face on the screen.

As the analysis revealed no difference in response time for different face types, dispositions, or following behaviour, it might seem that motor responses would not be considered an appropriate method for long gaze-leading studies. Furthermore, there does not appear to be a consistent group of participants that are influenced by the gaze of any face type, further suggesting that the method might be flawed. Although using motor responses in a gaze-leading study has some benefits over the more conventional approach of eye-tracking, with motor responses being a method that is less expensive, more accessible, and potentially easier to replicate, the findings of the present study indicate that eye-tracking remains the superior choice. However, it is possible

[1] An additional linear mixed model was analysed for only the data from the first half of the experiment, but none of the effects showed up as having an impact on response time (see Appendix A).

that motor responses could still be a viable method for shorter experiments, but more research is needed to determine if there is an ideal length for such an experiment.

Anthropomorphism and Likeability

Another aim of the study was to determine whether anthropomorphism and likeability were higher for faces that typically followed the participants' gaze. Anthropomorphism was found to be higher in human faces compared to robot and uncanny faces, which is an unsurprising finding considering anthropomorphism is related to how humanlike an entity is (Bartneck et al., 2009). Furthermore, anthropomorphism was found to be slightly higher for uncanny faces compared to robot faces. The two robot stimuli used in the study are of two rather mechanical-looking robots, whereas the two uncanny stimuli appear more human-like in appearance, which would explain why the uncanny robots would be rated higher in anthropomorphism.

A somewhat surprising finding was that anthropomorphism was found to be lower in the joint condition compared to the disjoint condition for human faces, meaning that human faces that typically do not follow gaze are perceived to be more humanlike than those that do follow gaze. On the other hand, robot faces were found to have a slightly higher likeability in the joint condition. However, it should be noted that these effects were not found to be particularly strong, with an estimate of only -0.1 and 0.09, respectively, with the measure being on a five-point rating scale. Furthermore, the graphical universality analysis revealed that there does not appear to be a clear pattern of anthropomorphism being different in the joint disposition compared to the disjoint disposition. The entire group of participants seemed about split in half where half the group indicated a higher anthropomorphism for the joint disposition, and the other half a higher anthropomorphism for the disjoint disposition. Nonetheless, it could be interesting to further examine whether these effects persist in similar studies.

Likeability was found to be higher in human faces compared to robot faces and uncanny faces. Between robot faces and uncanny faces, robot faces were found to have a higher likeability. It is not surprising that human faces were found to have the highest likeability, considering the human brain has an area that is specifically involved in perceiving human faces (Kanwisher et al., 1997). Furthermore, a recent study found that robot faces were perceived as less "face-like" compared to human faces (Momen et al., 2022), which could explain why human faces had the highest likeability out of all face types. It is also not surprising that mechanical robot faces were found to have a higher likeability than uncanny robot faces.

Additionally, likeability was found to be lower in the disjoint condition compared to the joint condition, but only for the robot face type, meaning that likeability is higher for a robot that typically follows gaze. This finding correlates with previous studies as likeability has previously been found to be higher in the joint condition compared to the disjoint condition in robot faces (Willemse et al., 2018). However, likeability was not found to be higher in the joint condition compared to the disjoint condition for the human- and uncanny face types, with the human face type surprisingly having a slightly higher likeability in the disjoint condition compared to the joint condition. This finding was unexpected as it has been theorised that having one's gaze followed induces likeability in the other agent (Bayliss et al., 2013). It is possible that this discrepancy could be due to the clicking behaviour of participants becoming automated and that participants no longer paid attention to the direction of the gaze after a certain point. However, it should be noted that the effect of human faces having a higher likeability in the disjoint condition was found to be very small, indicating that this finding might be negligible. Moreover, the graphical universality analysis indicated no clear pattern between participants, as, similar to the anthropomorphism scores, around half the participants indicated a higher likeability for the joint disposition, and the other half a higher score for the disjoint disposition. However, future research is needed to determine whether this is the case or if likeability does not increase in the joint condition for human and uncanny robot faces.

The Uncanny valley

The study was aimed at determining whether there would be a difference in both response times and in the self-report ratings of anthropomorphism and likeability for the human, robot, and uncanny face types. Both the uncanny- and robot faces were adapted from a study on the uncanny valley by Mathur et al. (2020) where the two uncanny faces used in this study were listed as being close to the low point in the uncanny valley. However, the average scores of likeability per face (see Appendix I) revealed that, although robot faces had a higher average likeability compared to uncanny faces, the second uncanny face had a likeability that was higher than both robot faces, in both the joint and disjoint condition. Although likeability is not the only important factor in determining whether a face is uncanny or not (Ho & MacDorman, 2010), it is still surprising that a robot face that is supposedly uncanny is more liked than robot faces that are not uncanny and it is possible that this could have had an effect on the comparison of the different face types.

Limitations and Future Studies

One of the main limitations of this study is that the experiment was conducted using motor responses instead of using eye tracking. Although motor responses have previously been found to be a suitable substitute for eye tracking in gaze-leading studies (Willemse et al., 2022), using clicking is still a further step away from the actual behaviour, namely gaze-leading. Using eye tracking better mimics the actual behaviour and is, therefore, a better-suited method for gaze-leading studies. Thus, a suggestion for future research is to conduct a similar experiment by using a within-subjects comparison of different face types with eye tracking instead of motor responses to determine whether eye tracking would reveal differences in the time of the return saccade to the different face types.

Furthermore, it is possible that the length of the experiment impacted the results, namely by resulting in the clicking behaviour of participants possibly becoming automated. Thus, a shorter experiment, such as the experiment in the study by Willemse et al. (2022), might be more suitable when using motor responses. Nonetheless, future studies could investigate at what point behaviour in a motor response experiment is likely to become automated to determine how long such an experiment should be for there to be any effect from gaze cues. A suggestion is to conduct a motor response gaze-leading study using neuroimaging. Several studies have shown that brain activity is lower for automatic behaviours (Wu et al., 2004; Poldrack et al., 2005), meaning that a neuroimaging study might reveal when the motor response behaviour in a gaze-leading study becomes automatic.

Another limitation to mention is that the experiment used faces displayed on a computer screen to simulate social interaction. Although some forms of interaction do occur through a computer screen, such as when interacting with a virtual character, most forms of social interaction occur with a physical entity. Thus, it would be beneficial to investigate the effects of gaze-leading using, for example, a physical robot to reveal how gaze-leading effects might occur in a real-life setting.

By using motor responses, another limitation is that it becomes difficult to distinguish whether the lack of effects observed in the results is due to whether the observed effect of gaze found in prior studies does not exist or whether the method used in the present study is flawed. It does seem unlikely that an effect that has been found in several studies and replicated several times does not exist. Moreover, there are several indications of the method being flawed, such as the clicking behaviour becoming more rhythmic and less varied as the experiment progressed, indicating that the behaviour of participants became automated. Thus, although it is not possible to say with full certainty whether the lack of observed effects is due to the method, it does appear to be the case that the method is flawed.

Lastly, a limitation of the study was the selection of the faces for the stimuli. As mentioned, one of the uncanny faces had a likeability that was higher than both robot faces, in both the joint and disjoint condition. Therefore, for future studies aiming to compare different face types, it would be advisable to conduct a short pilot study to determine whether an uncanny face falls into that category or not.

Conclusion

Contrary to prior studies, this study did not reveal any differences in the return time to re-establish attention on faces that typically follow gaze compared to faces that do not typically follow gaze. Moreover, no difference in return times was observed between the human, robot, and uncanny face types. It is possible that using motor responses can have caused the behaviour of participants to become automated, negating any effects of the gaze of the faces. Similarly, likeability and anthropomorphism were not found to be consistently higher for faces that follow, which again could be due to automated behaviour. The results of the study indicate that using long motor response experiments to study gaze leading might not be an ideal method.

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Appendix A

R Markdown of Data Analysis

Data Analysis

Ingvild Kvalsvik

2024-05-24

Installing packages

```
library(tidyverse)

## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.
0.0 ──
## ✔ dplyr     1.1.2     ✔ readr     2.1.4
## ✔ forcats   1.0.0     ✔ stringr   1.5.0
## ✔ ggplot2   3.4.2     ✔ tibble    3.2.1
## ✔ lubridate 1.9.2     ✔ tidyr     1.3.0
## ✔ purrr     1.0.1
## ── Conflicts ──────────────────────────────────────────── tidyverse_conflict
s() ──
## ✖ dplyr::filter() masks stats::filter()
## ✖ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force al
l conflicts to become errors

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 4.3.2
```

Preparing data

```
prepare_data <- function(file_path) {
  data <- read_csv(file_path) %>%
    #getting relevant columns from csv file
    select(participant, list, trials.thisN, Following, Face, mouse_face_trial
```

```
.time) %>%
    #removing data from practice /trial (first 9 rows)
    slice(9:n()) %>%
     mutate(
       #removing brackets from the mouse_face_trial.time column
      mouse_face_trial.time = gsub("\\[|\\]", "", mouse_face_trial.time) %>%
as.numeric,
      # i wanted to compare RTs of first half of experiment vs second half of
experiment so adding a column for that
      half = ifelse(row_number() <= n() / 2, "first_half", "second_half"),
      #we want RT in ms so adding a column "RT"
      RT = round(mouse_face_trial.time * 1000)
    ) %>%
    #cutting off very short and very long responses
    #cutoff larger than 2000 ms
    #lower boundary:less than 100 ms
    filter(RT >= 100 & RT <= 2000)
  return(data)
}

# Listing all the csv files
csv_files <- list.files(pattern = "\\.csv$")

# Apply the function to each csv file

#Note: the output of the following line of code was removed as it did not add
any relevant information and took up several pages
list_of_data <- lapply(csv_files, prepare_data)

# Combining data into one data frame
combined_data <- bind_rows(list_of_data)

# Adding disposition as a column (joint / disjoint)
#for participants in list 1, the "1" faces were in joint disposition and "2"
faces in disjoint
#and the opposite for list 2 (face1 = disjoint, face2 = joint)
combined_data <- combined_data %>%
  mutate(disposition = case_when(
    (list == 1 & (Face == "human1" | Face == "robot1" | Face == "uncanny1"))
~ "joint",
    (list == 1 & (Face == "human2" | Face == "robot2" | Face == "uncanny2"))
~ "disjoint",
    (list == 2 & (Face == "human1" | Face == "robot1" | Face == "uncanny1"))
~ "disjoint",
    (list == 2 & (Face == "human2" | Face == "robot2" | Face == "uncanny2"))
~ "joint",
    TRUE ~ NA_character_
  ))

#adding a column with only facetype instead of each separate face
```

```
combined_data <- combined_data %>%
  mutate(facetype = case_when(
    (Face == "human1" | Face == "human2") ~ "human",
    (Face == "robot1" | Face == "robot2") ~ "robot",
    (Face == "uncanny1" | Face == "uncanny2") ~ "uncanny",
    TRUE ~ NA_character_
  )
         )
```

Qualtrics data

Note: Hand: 1 = left handed 2 = right handed

Gender: 1 = male 2 = female 3 = other

```
#importing qualtrics data
qualtrics_data <- read_csv("qualtrics/qualtrics.csv") %>%
   select(participant, Hand, Gender, Age, human1_avg_anthro, human1_avg_like,
human2_avg_anthro, human2_avg_like, robot1_avg_anthro, robot1_avg_like, robot
2_avg_anthro, robot2_avg_like, uncanny1_avg_anthro, uncanny1_avg_like, uncann
y2_avg_anthro, uncanny2_avg_like)%>%
   slice(2:n()) %>%
  mutate(across(c(Hand, Gender, Age), as.numeric))

## Rows: 36 Columns: 109
## ── Column specification ──────────────────────────────────────────────────
──────

## Delimiter: ","
## chr (97): StartDate, EndDate, Status, IPAddress, Progress, Duration (in se
co...
## dbl (12): human1_avg_anthro, human1_avg_like, human2_avg_anthro, human2_av
g_...
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this
message.

str(qualtrics_data)

## tibble [35 × 16] (S3: tbl_df/tbl/data.frame)
##  $ participant       : chr [1:35] "201" "202" "203" "204" ...
##  $ Hand              : num [1:35] NA NA 2 2 2 2 2 2 2 2 ...
##  $ Gender            : num [1:35] 1 1 1 1 1 1 1 1 1 2 ...
##  $ Age               : num [1:35] 21 23 21 22 23 21 23 26 21 25 ...
##  $ human1_avg_anthro : num [1:35] 3.4 3.8 3.2 2.6 3.4 4 3.8 4.4 5 5 ...
##  $ human1_avg_like   : num [1:35] 4 3.2 2.6 2.8 3.8 3.8 4 4.2 3 4.2 ...
##  $ human2_avg_anthro : num [1:35] 2.4 3.2 4.6 3.4 3 3.4 4 4.8 4.6 5 ...
##  $ human2_avg_like   : num [1:35] 3.8 2.6 4.6 2.4 3.2 2.8 2.6 4.2 3 3.6 .
..
##  $ robot1_avg_anthro : num [1:35] 1.2 1.4 2 1 1.8 1 1.2 1.2 1 1.8 ...
```

```
##  $ robot1_avg_like    : num [1:35] 1.8 3.8 2.8 1.8 2.8 2.4 2.6 2.4 3 4.2 .
..
##  $ robot2_avg_anthro  : num [1:35] 1.4 2 2.4 1 2.2 1.2 1.4 1.4 1 2.8 ...
##  $ robot2_avg_like    : num [1:35] 2.6 3.8 2.6 1 2 2.2 3.6 2.4 3 4.6 ...
##  $ uncanny1_avg_anthro: num [1:35] 1.6 2 3.4 1.6 1.8 1.2 2.6 1.4 1 2.2 ...
##  $ uncanny1_avg_like  : num [1:35] 2 3.4 2.8 1.8 2.2 2.2 3.2 3 1.4 2.6 ...
##  $ uncanny2_avg_anthro: num [1:35] 1.6 2.2 2 1 2.4 1 2 2 1.4 2.6 ...
##  $ uncanny2_avg_like  : num [1:35] 2.8 3.8 3.2 1.6 3.6 2.8 4.2 3.6 2.4 3 .
..
```

Making one big dataset

```
psychopy_qualtrics <- merge(combined_data, qualtrics_data, by = "participant"
, all.x = TRUE) %>%
  #removing hand, age, and gender
  select(-Hand, -Age, - Gender)

head(psychopy_qualtrics)
```

```
##   participant list trials.thisN  Following     Face mouse_face_trial.time
## 1         201    1            1   followed   human1             0.8914420
## 2         201    1            2   followed   human1             0.9043974
## 3         201    1            3 unfollowed   robot2             1.0426715
## 4         201    1            4   followed   human1             0.8215317
## 5         201    1            5 unfollowed uncanny1             1.3960668
## 6         201    1            6   followed   robot1             1.1541242
##         half   RT disposition facetype human1_avg_anthro human1_avg_like
## 1 first_half  891       joint    human               3.4               4
## 2 first_half  904       joint    human               3.4               4
## 3 first_half 1043    disjoint    robot               3.4               4
## 4 first_half  822       joint    human               3.4               4
## 5 first_half 1396       joint  uncanny               3.4               4
## 6 first_half 1154       joint    robot               3.4               4
##   human2_avg_anthro human2_avg_like robot1_avg_anthro robot1_avg_like
## 1               2.4             3.8               1.2             1.8
## 2               2.4             3.8               1.2             1.8
## 3               2.4             3.8               1.2             1.8
## 4               2.4             3.8               1.2             1.8
## 5               2.4             3.8               1.2             1.8
## 6               2.4             3.8               1.2             1.8
##   robot2_avg_anthro robot2_avg_like uncanny1_avg_anthro uncanny1_avg_like
## 1               1.4             2.6                 1.6                 2
## 2               1.4             2.6                 1.6                 2
## 3               1.4             2.6                 1.6                 2
## 4               1.4             2.6                 1.6                 2
## 5               1.4             2.6                 1.6                 2
## 6               1.4             2.6                 1.6                 2
##   uncanny2_avg_anthro uncanny2_avg_like
## 1                 1.6               2.8
## 2                 1.6               2.8
```

```
## 3                    1.6                 2.8
## 4                    1.6                 2.8
## 5                    1.6                 2.8
## 6                    1.6                 2.8

#adding anthropomorphism scores for each face
everything_data_anthro <- psychopy_qualtrics %>%
  mutate(Anthropomorphism = case_when(
    Face == "human1" ~ human1_avg_anthro,
    Face == "human2" ~ human2_avg_anthro,
    Face == "robot1" ~ robot1_avg_anthro,
    Face == "robot2" ~ robot2_avg_anthro,
    Face == "uncanny1" ~ uncanny1_avg_anthro,
    Face == "uncanny2" ~ uncanny2_avg_anthro,
    TRUE ~ NA_real_
  ))

#addding likeability scores for each face
everything_data <- everything_data_anthro %>%
  mutate(Likeability = case_when(
    Face == "human1" ~ human1_avg_like,
    Face == "human2" ~ human2_avg_like,
    Face == "robot1" ~ robot1_avg_like,
    Face == "robot2" ~ robot2_avg_like,
    Face == "uncanny1" ~ uncanny1_avg_like,
    Face == "uncanny2" ~ uncanny2_avg_like,
    TRUE ~ NA_real_
  ))
```

Descriptive statistics

Demographics

```
#in total, 35 participants (1 response deleted because not full response)

count_hand <- table(qualtrics_data$Hand)
print(count_hand)

##
##  1  2
##  3 30

# 3 left handed, 30 right handed (missing data for 2 participants)

count_gender <- table(qualtrics_data$Gender)
print(count_gender)

##
##  1  2
## 20 15
```

```
# 20 male, 15 female


avg_age <- mean(qualtrics_data$Age, na.rm = TRUE)
print(avg_age)

## [1] 24.85714

# mean age = 24.86

sd_age <- sd(qualtrics_data$Age, na.rm = TRUE)
print(sd_age)

## [1] 10.13481

# SD age = 10.56

median_age <- median(qualtrics_data$Age, na.rm = TRUE)
print(median_age)

## [1] 22

# median age = 22
```

Looking at some average RTs

```
#average response time per participant
average_response_time_participant <- combined_data %>%
  group_by(participant) %>%
  summarize(avg_mouse_face_time = mean(RT, na.rm = TRUE))
print(average_response_time_participant)

## # A tibble: 35 × 2
##    participant avg_mouse_face_time
##          <dbl>               <dbl>
##  1         201                823.
##  2         202                620.
##  3         203               1017.
##  4         204                775.
##  5         205                724.
##  6         206                770.
##  7         207                929.
##  8         208                794.
##  9         209                787.
## 10         210                623.
## # ℹ 25 more rows

#avg response time overall -> give an idea for cutoffs
average_response <- combined_data %>%
  summarize(avg_mouse_face_time = mean(RT, na.rm = TRUE))
print(average_response)
```

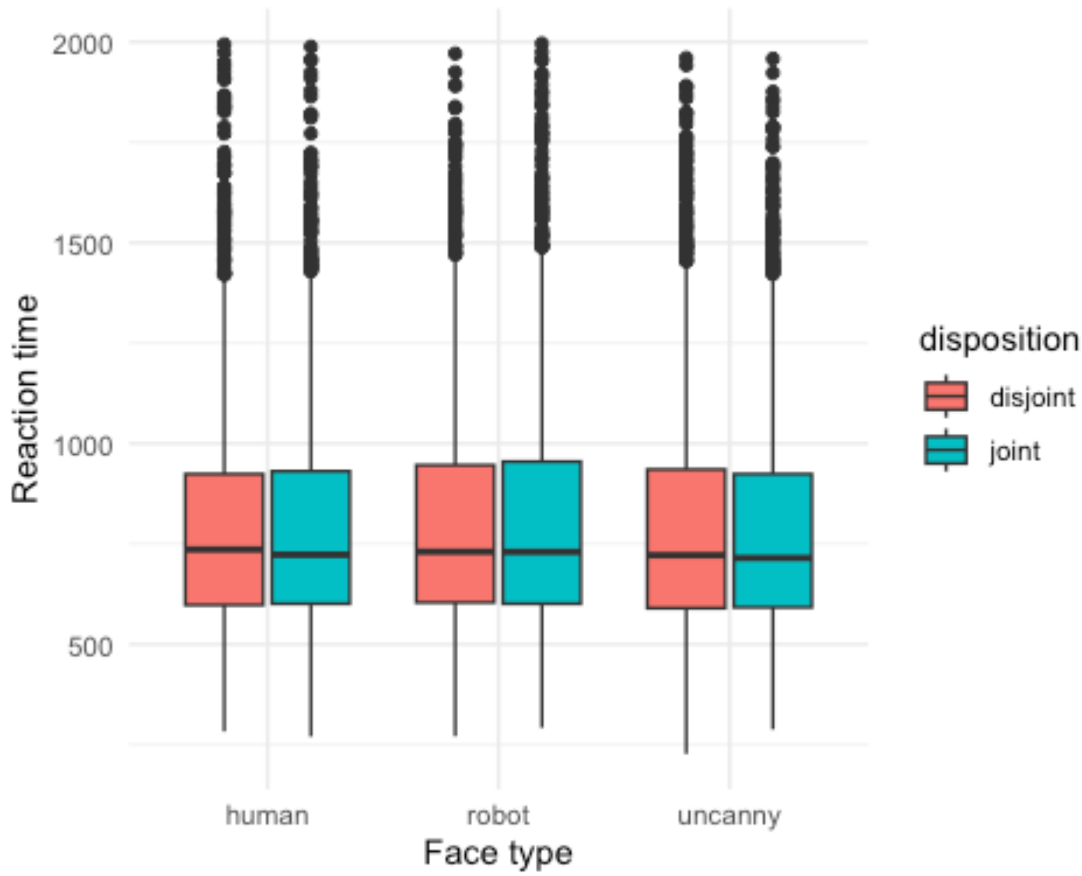
```
## # A tibble: 1 × 1
##   avg_mouse_face_time
##                 <dbl>
## 1                792.

#avg response time per participant of first and second half
average_response_time_first_second_half_perparticipant <- combined_data %>%
  group_by(participant, half) %>%
  summarize(avg_mouse_face_time = mean(RT, na.rm = TRUE))

## `summarise()` has grouped output by 'participant'. You can override using
the
## `.groups` argument.

print(average_response_time_first_second_half_perparticipant)

## # A tibble: 70 × 3
## # Groups:   participant [35]
##    participant half        avg_mouse_face_time
##          <dbl> <chr>                     <dbl>
##  1         201 first_half                 850.
##  2         201 second_half                799.
##  3         202 first_half                 660.
##  4         202 second_half                580.
##  5         203 first_half                1159.
##  6         203 second_half                875.
##  7         204 first_half                 812.
##  8         204 second_half                740.
##  9         205 first_half                 737.
## 10         205 second_half                711.
## # ℹ 60 more rows

#avg response time and sd for first half and second half
average_response_time_first_second_half <- combined_data %>%
  group_by(half) %>%
  summarize(
    avg_mouse_face_time = mean(RT, na.rm = TRUE),
    sd_mouse_face_time = sd(RT, na.rm = TRUE)
  )
print(average_response_time_first_second_half)

## # A tibble: 2 × 3
##   half        avg_mouse_face_time sd_mouse_face_time
##   <chr>                     <dbl>              <dbl>
## 1 first_half                 843.               287.
## 2 second_half                742.               248.

#avg response time for each face for each participant
average_response_time_face <- combined_data %>%
  group_by(participant, Face) %>%
  summarize(avg_mouse_face_time = mean(RT, na.rm = TRUE))
```

```
## `summarise()` has grouped output by 'participant'. You can override using
the
## `.groups` argument.

print(average_response_time_face)

## # A tibble: 210 × 3
## # Groups:   participant [35]
##    participant Face     avg_mouse_face_time
##          <dbl> <chr>                  <dbl>
##  1         201 human1                  820.
##  2         201 human2                  788.
##  3         201 robot1                  821.
##  4         201 robot2                  837.
##  5         201 uncanny1                864.
##  6         201 uncanny2                813.
##  7         202 human1                  623.
##  8         202 human2                  614.
##  9         202 robot1                  643.
## 10         202 robot2                  620.
## # ℹ 200 more rows

#avg response time for each face for each list
average_response_time_face_list <- combined_data %>%
  group_by(list, Face) %>%
  summarize(avg_mouse_face_time = mean(RT, na.rm = TRUE))

## `summarise()` has grouped output by 'list'. You can override using the
## `.groups` argument.

print(average_response_time_face_list)

## # A tibble: 12 × 3
## # Groups:   list [2]
##     list Face     avg_mouse_face_time
##    <dbl> <chr>                  <dbl>
##  1     1 human1                  821.
##  2     1 human2                  827.
##  3     1 robot1                  834.
##  4     1 robot2                  833.
##  5     1 uncanny1                818.
##  6     1 uncanny2                829.
##  7     2 human1                  760.
##  8     2 human2                  758.
##  9     2 robot1                  764.
## 10     2 robot2                  765.
## 11     2 uncanny1                757.
## 12     2 uncanny2                760.

#avg response time for each face type per list
average_response_time_facetype <- combined_data %>%
```

```
  group_by(facetype) %>%
  summarize(RT = mean(RT, na.rm = TRUE))
print(average_response_time_facetype)

## # A tibble: 3 × 2
##   facetype    RT
##   <chr>    <dbl>
## 1 human     790.
## 2 robot     797.
## 3 uncanny   789.

average_response_time_facetype_dispo <- combined_data %>%
  group_by(facetype, disposition) %>%
  summarize(RT = mean(RT, na.rm = TRUE))

## `summarise()` has grouped output by 'facetype'. You can override using the
## `.groups` argument.

print(average_response_time_facetype_dispo)

## # A tibble: 6 × 3
## # Groups:   facetype [3]
##   facetype disposition    RT
##   <chr>    <chr>       <dbl>
## 1 human    disjoint     792.
## 2 human    joint        788.
## 3 robot    disjoint     797.
## 4 robot    joint        798.
## 5 uncanny  disjoint     791.
## 6 uncanny  joint        787.
```

Plot Average RT for each face type and disposition

```
ggplot(combined_data, aes(x = facetype, y = RT, fill = disposition)) +
  geom_boxplot() +
  labs(x = "Face type", y = "Reaction time") +
  theme_minimal()
```



LMM for RT

```
model_3 <- lmer(RT ~ Following * disposition * facetype + (1 | participant),
data = combined_data)
summary(model_3)

## Linear mixed model fit by REML ['lmerMod']
## Formula: RT ~ Following * disposition * facetype + (1 | participant)
##    Data: combined_data
##
## REML criterion at convergence: 207892.6
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.7687 -0.6383 -0.1965  0.4062  6.1956
##
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  participant (Intercept) 26328    162.3
##  Residual                48282    219.7
## Number of obs: 15253, groups:  participant, 35
##
## Fixed effects:
```

```
##                                                        Estimate Std. Error
## (Intercept)                                             796.553     29.142
## Followingunfollowed                                     -10.962     10.985
## dispositionjoint                                        -13.418     10.978
## facetyperobot                                           -13.596     13.857
## facetypeuncanny                                          -8.345     13.785
## Followingunfollowed:dispositionjoint                      6.611     15.433
## Followingunfollowed:facetyperobot                        22.703     15.480
## Followingunfollowed:facetypeuncanny                       8.979     15.409
## dispositionjoint:facetyperobot                           21.437     15.470
## dispositionjoint:facetypeuncanny                          9.010     15.410
## Followingunfollowed:dispositionjoint:facetyperobot      -16.915     21.828
## Followingunfollowed:dispositionjoint:facetypeuncanny  -13.811     21.772
##                                                       t value
## (Intercept)                                            27.334
## Followingunfollowed                                    -0.998
## dispositionjoint                                       -1.222
## facetyperobot                                          -0.981
## facetypeuncanny                                        -0.605
## Followingunfollowed:dispositionjoint                    0.428
## Followingunfollowed:facetyperobot                       1.467
## Followingunfollowed:facetypeuncanny                     0.583
## dispositionjoint:facetyperobot                          1.386
## dispositionjoint:facetypeuncanny                        0.585
## Followingunfollowed:dispositionjoint:facetyperobot     -0.775
## Followingunfollowed:dispositionjoint:facetypeuncanny  -0.634
##
## Correlation of Fixed Effects:
##                                (Intr) Fllwng dspstn fctypr fctypn Fllwngnfl
lwd:d
## Fllwngnfllw                    -0.303
## dispostnjnt                    -0.303  0.804
## facetyperbt                    -0.240  0.637  0.637
## factypncnny                    -0.241  0.640  0.641  0.508
## Fllwngnfllwd:d                  0.216 -0.712 -0.711 -0.453 -0.456
## Fllwngnfllwd:fctypr             0.215 -0.710 -0.571 -0.895 -0.454  0.505
## Fllwngnfllwd:fctypn             0.216 -0.713 -0.573 -0.454 -0.895  0.507
## dspstnjnt:fctypr                0.215 -0.571 -0.710 -0.896 -0.455  0.505
## dspstnjnt:fctypn                0.216 -0.573 -0.712 -0.454 -0.895  0.507
## Fllwngnfllwd:dspstnjnt:fctypr -0.152  0.503  0.503  0.635  0.322 -0.707
## Fllwngnfllwd:dspstnjnt:fctypn -0.153  0.505  0.504  0.321  0.633 -0.709
##                                Fllwngnfllwd:fctypr Fllwngnfllwd:fctypn
## Fllwngnfllw
## dispostnjnt
## facetyperbt
## factypncnny
## Fllwngnfllwd:d
## Fllwngnfllwd:fctypr
## Fllwngnfllwd:fctypn             0.506
## dspstnjnt:fctypr                0.802               0.407
```

```
## dspstnjnt:fctypn               0.407                0.800
## Fllwngnfllwd:dspstnjnt:fctypr -0.709               -0.359
## Fllwngnfllwd:dspstnjnt:fctypn -0.358               -0.708
##                               dspstnjnt:fctypr dspstnjnt:fctypn
## Fllwngnfllw
## dispostnjnt
## facetyperbt
## factypncnny
## Fllwngnfllwd:d
## Fllwngnfllwd:fctypr
## Fllwngnfllwd:fctypn
## dspstnjnt:fctypr
## dspstnjnt:fctypn               0.506
## Fllwngnfllwd:dspstnjnt:fctypr -0.709           -0.358
## Fllwngnfllwd:dspstnjnt:fctypn -0.358           -0.708
##                               Fllwngnfllwd:dspstnjnt:fctypr
## Fllwngnfllw
## dispostnjnt
## facetyperbt
## factypncnny
## Fllwngnfllwd:d
## Fllwngnfllwd:fctypr
## Fllwngnfllwd:fctypn
## dspstnjnt:fctypr
## dspstnjnt:fctypn
## Fllwngnfllwd:dspstnjnt:fctypr
## Fllwngnfllwd:dspstnjnt:fctypn  0.501
```

Making a table with fixed effects, SEs, and getting confidence intervals

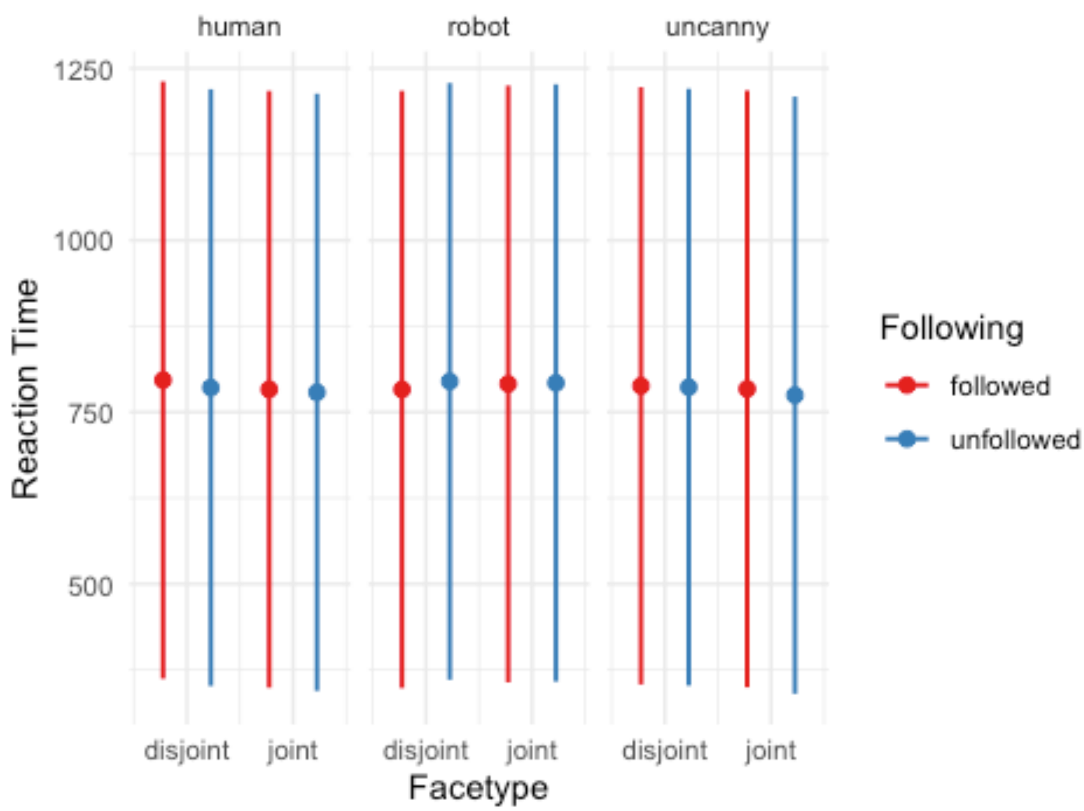
```
summary_fixed <- summary(model_3)$coefficients

#fixed effects
fixed_effects_estimates <- summary_fixed[, "Estimate"]

#SEs
standard_errors <- summary_fixed[, "Std. Error"]

# create data frame
fixed_effects_table <- data.frame(
  Fixed_Effects = rownames(summary_fixed),
  Estimate = fixed_effects_estimates,
  `Std. Error` = standard_errors
)
print(fixed_effects_table)

##
Fixed_Effects
## (Intercept)
(Intercept)
```

```
## Followingunfollowed
Followingunfollowed
## dispositionjoint
dispositionjoint
## facetyperobot
facetyperobot
## facetypeuncanny
facetypeuncanny
## Followingunfollowed:dispositionjoint                                   Follo
wingunfollowed:dispositionjoint
## Followingunfollowed:facetyperobot                                        Fo
llowingunfollowed:facetyperobot
## Followingunfollowed:facetypeuncanny                                     Foll
owingunfollowed:facetypeuncanny
## dispositionjoint:facetyperobot
dispositionjoint:facetyperobot
## dispositionjoint:facetypeuncanny                                          d
ispositionjoint:facetypeuncanny
## Followingunfollowed:dispositionjoint:facetyperobot     Followingunfollowed
:dispositionjoint:facetyperobot
## Followingunfollowed:dispositionjoint:facetypeuncanny Followingunfollowed:d
ispositionjoint:facetypeuncanny
##                                                        Estimate Std..Error
## (Intercept)                                          796.553475   29.14159
## Followingunfollowed                                  -10.962224   10.98511
## dispositionjoint                                     -13.417883   10.97836
## facetyperobot                                        -13.595861   13.85741
## facetypeuncanny                                       -8.345000   13.78472
## Followingunfollowed:dispositionjoint                   6.611368   15.43259
## Followingunfollowed:facetyperobot                     22.703093   15.48021
## Followingunfollowed:facetypeuncanny                    8.979293   15.40861
## dispositionjoint:facetyperobot                        21.436661   15.46979
## dispositionjoint:facetypeuncanny                       9.010384   15.40961
## Followingunfollowed:dispositionjoint:facetyperobot   -16.914963   21.82829
## Followingunfollowed:dispositionjoint:facetypeuncanny -13.811267   21.77217

#confidence intervals
fixed_confint <- confint(model_3, level = 0.95)

## Computing profile confidence intervals ...

print(fixed_confint)

##                                                           2.5 %    97.5 %
## .sig01                                               128.531100 206.34763
## .sigma                                               217.207893 222.14365
## (Intercept)                                          738.910516 854.19138
## Followingunfollowed                                  -32.486926  10.56106
## dispositionjoint                                     -34.929081   8.09246
## facetyperobot                                        -40.748581  13.55528
## facetypeuncanny                                      -35.355156  18.66384
```

```
## Followingunfollowed:dispositionjoint                     -23.626107  36.85050
## Followingunfollowed:facetyperobot                         -7.627454  53.03575
## Followingunfollowed:facetypeuncanny                      -21.211181  39.17145
## dispositionjoint:facetyperobot                            -8.873536  51.74883
## dispositionjoint:facetypeuncanny                         -21.182263  39.20427
## Followingunfollowed:dispositionjoint:facetyperobot       -59.686235  25.85356
## Followingunfollowed:dispositionjoint:facetypeuncanny -56.471893  28.84798
```

Plotting model

```
ggpredict(model_3, terms = c("disposition", "Following", "facetype"), type =
"re") %>%
   plot(dodge = 0.9) +
   labs(x = "Facetype", y = "Reaction Time", title = "") +
   theme_minimal()
```



Looking at universality

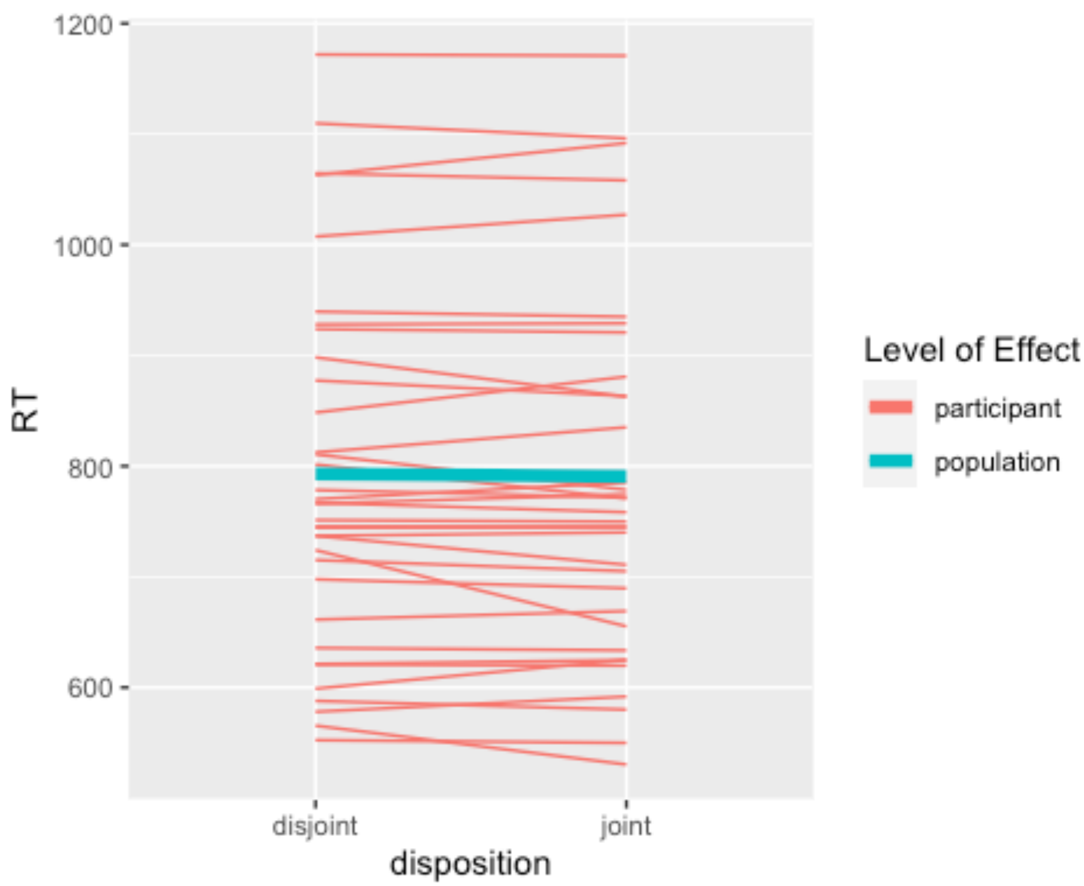
Disposition

```
combined_data %>%
  ggplot(aes(
    x = disposition,
```

```
    y = RT,
    group = participant
  )) +
  geom_smooth(aes(color = "participant"),
    size = .5, se = F, method = "lm"
  ) +
  geom_smooth(aes(group = 1, color = "population"),
    size = 2, se = F, method = "lm"
  ) +
  labs(color = "Level of Effect")
```

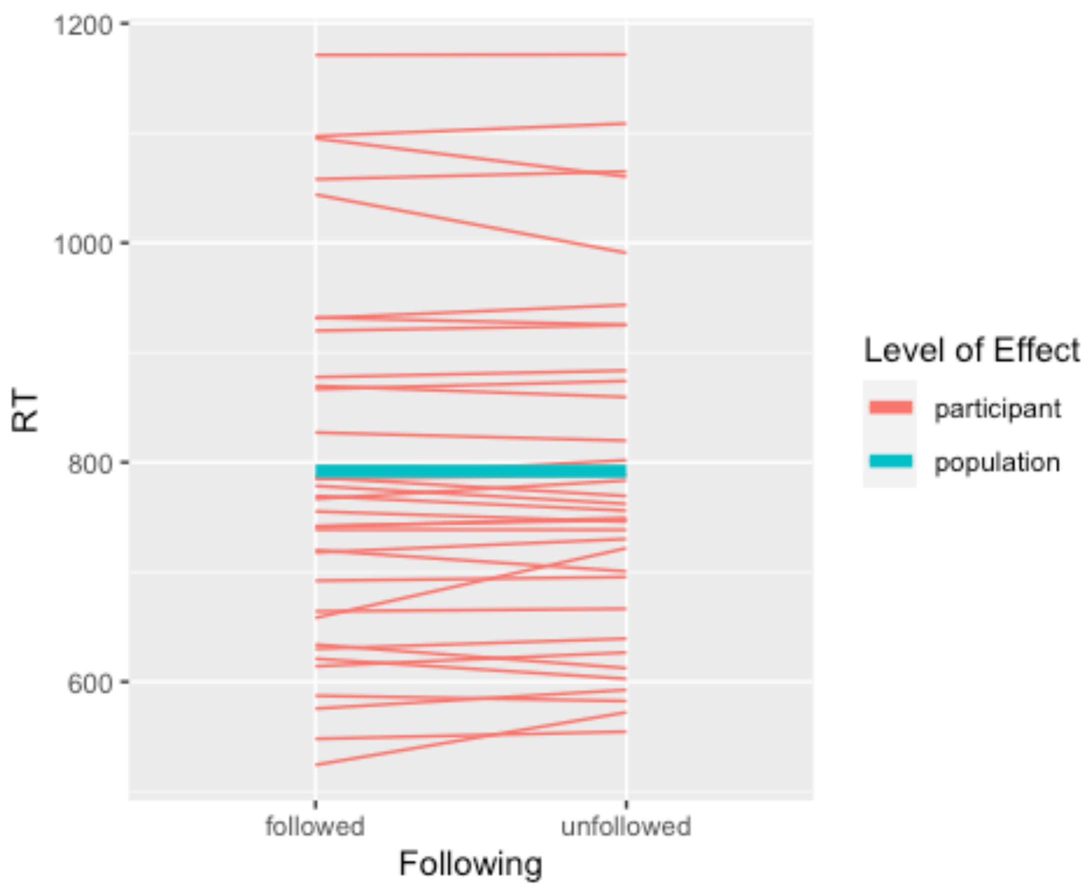
```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## ℹ Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```



Following behaviour

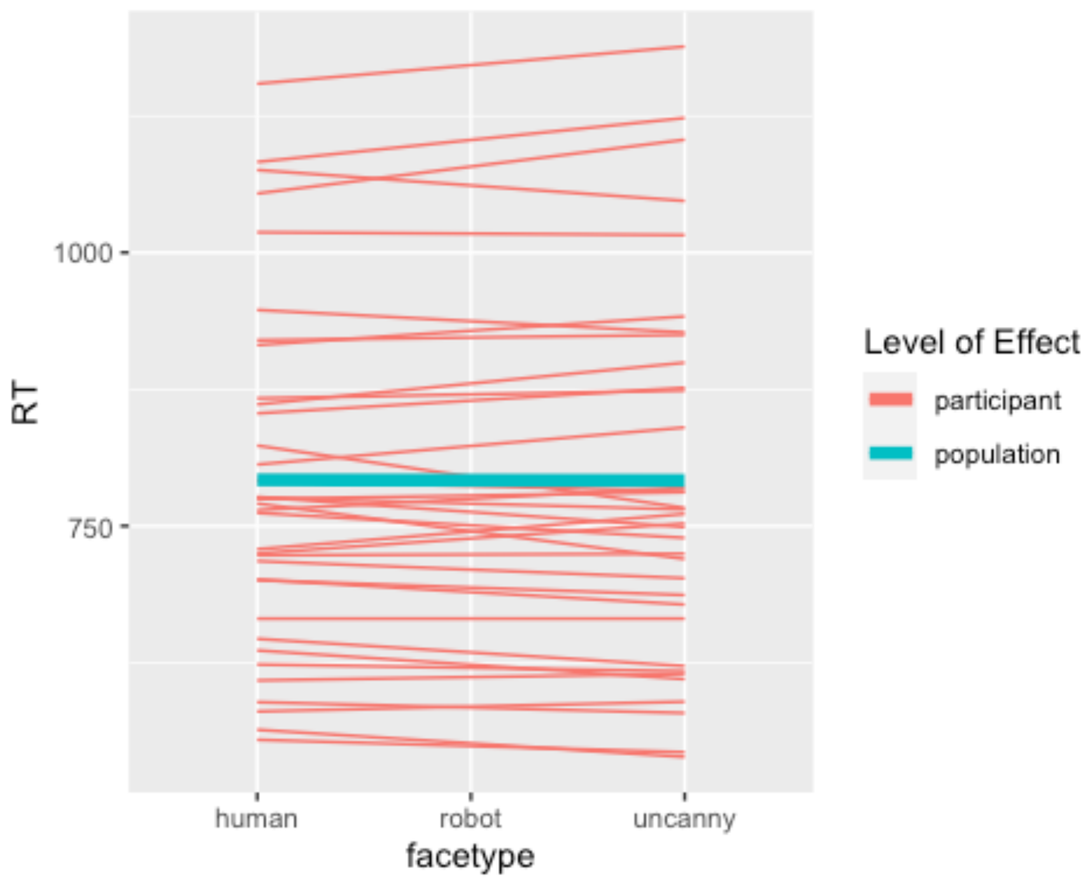
```
combined_data %>%
  ggplot(aes(
    x = Following,
    y = RT,
    group = participant
  )) +
  geom_smooth(aes(color = "participant"),
    size = .5, se = F, method = "lm"
  ) +
  geom_smooth(aes(group = 1, color = "population"),
    size = 2, se = F, method = "lm"
  ) +
  labs(color = "Level of Effect")

## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```



Facetype

```
combined_data %>%
  ggplot(aes(
```

```
    x = facetype,
    y = RT,
    group = participant
  )) +
  geom_smooth(aes(color = "participant"),
    size = .5, se = F, method = "lm"
  ) +
  geom_smooth(aes(group = 1, color = "population"),
    size = 2, se = F, method = "lm"
  ) +
  labs(color = "Level of Effect")

## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```



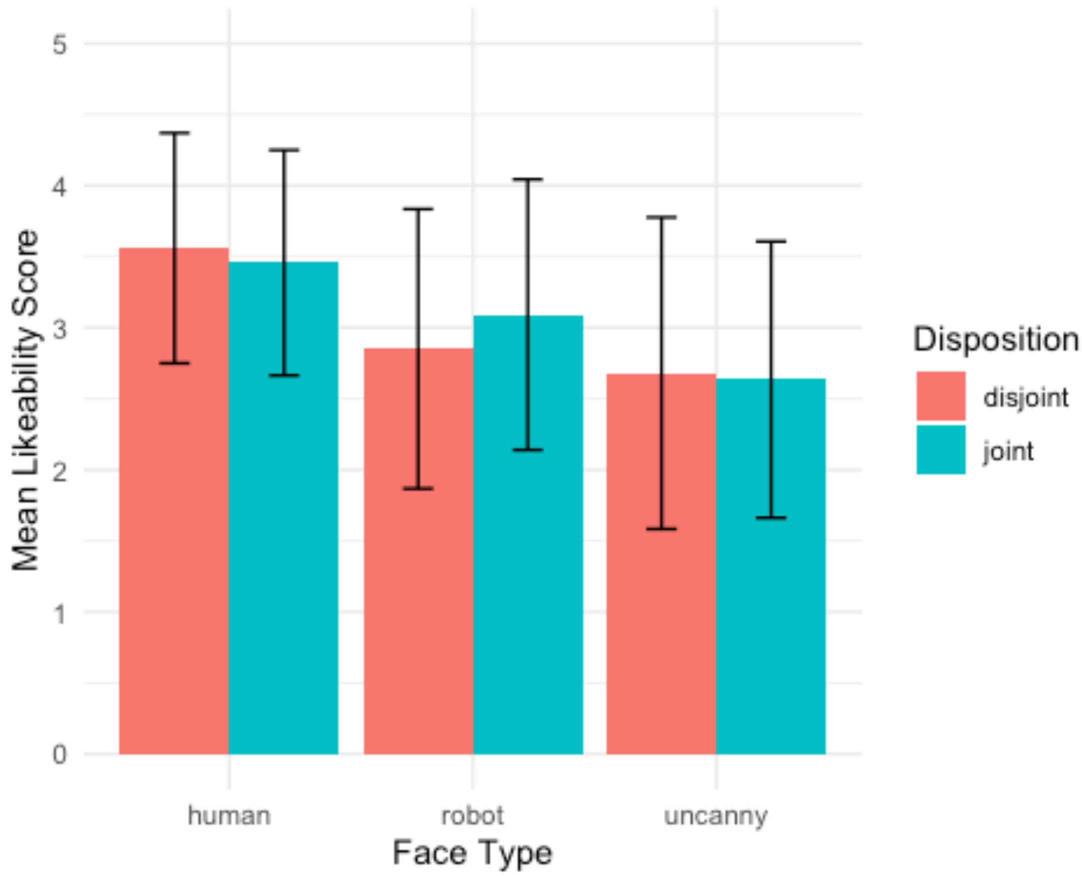
Likeability

```
#getting only one likeability score per face per participant to make it a bit
easier to handle
likelike <- everything_data %>%
  select(participant,facetype, disposition, Likeability) %>%
  group_by(facetype)
```

```
likelike <- likelike %>%
  distinct()

print(likelike)

## # A tibble: 210 × 4
## # Groups:   facetype [3]
##    participant facetype disposition Likeability
##          <dbl> <chr>    <chr>             <dbl>
##  1         201 human    joint               4
##  2         201 robot    disjoint            2.6
##  3         201 uncanny  joint               2
##  4         201 robot    joint               1.8
##  5         201 uncanny  disjoint            2.8
##  6         201 human    disjoint            3.8
##  7         202 human    joint               2.6
##  8         202 robot    joint               3.8
##  9         202 uncanny  joint               3.8
## 10         202 robot    disjoint            3.8
## # ℹ 200 more rows
```

Bar plot likeability

```
# Calculate mean and standard deviation for Likeability by facetype and dispo
sition
likelike_summary <- likelike %>%
  group_by(facetype, disposition) %>%
  summarise(mean_likeability = mean(Likeability),
            sd_likeability = sd(Likeability))

## `summarise()` has grouped output by 'facetype'. You can override using the
## `.groups` argument.

#bar plot with error bars
ggplot(likelike_summary, aes(x = facetype, y = mean_likeability, fill = dispo
sition)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_errorbar(aes(ymin = mean_likeability - sd_likeability, ymax = mean_lik
eability + sd_likeability),
                position = position_dodge(width = 0.9), width = 0.25) +
  labs(x = "Face Type", y = "Mean Likeability Score", fill = "Disposition") +
  ylim(0,5) +
  theme_minimal()
```



LMM likeability

```
model_like <- lmer(Likeability ~ facetype * disposition + (1 | participant),
                   data = everything_data)
summary(model_like)

## Linear mixed model fit by REML ['lmerMod']
## Formula: Likeability ~ facetype * disposition + (1 | participant)
##    Data: everything_data
##
## REML criterion at convergence: 36693.1
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.3971 -0.6658  0.0707  0.6088  2.6488
##
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  participant (Intercept) 0.2203   0.4693
##  Residual                0.6405   0.8003
## Number of obs: 15253, groups:  participant, 35
##
## Fixed effects:
```

```
##                                    Estimate Std. Error t value
## (Intercept)                         3.55554    0.08091  43.943
## facetyperobot                      -0.70081    0.02249 -31.156
## facetypeuncanny                    -0.86676    0.02243 -38.638
## dispositionjoint                   -0.09722    0.02241  -4.337
## facetyperobot:dispositionjoint      0.32064    0.03175  10.099
## facetypeuncanny:dispositionjoint    0.02367    0.03172   0.746
##
## Correlation of Fixed Effects:
##             (Intr) fctypr fctypn dspstn fctypr:
## facetyperbt -0.139
## factypncnny -0.139  0.501
## dispostnjnt -0.139  0.501  0.502
## fctyprbt:ds  0.098 -0.708 -0.355 -0.706
## fctypncnny:  0.098 -0.354 -0.707 -0.707  0.499
```

Results model likeability

```
summary_fixed_like <- summary(model_like)$coefficients

#fixed effects
fixed_effects_estimates_like <- summary_fixed_like[, "Estimate"]

#standard errors
standard_errors_like <- summary_fixed_like[, "Std. Error"]

# Create a data frame for reporting
fixed_effects_table_like <- data.frame(
  Fixed_Effects = rownames(summary_fixed_like),
  Estimate = fixed_effects_estimates_like,
  `Std. Error` = standard_errors_like
)

print(fixed_effects_table_like)

##                                                      Fixed_Effects    Estim
ate
## (Intercept)                                            (Intercept)  3.55554
142
## facetyperobot                                        facetyperobot -0.70081
497
## facetypeuncanny                                    facetypeuncanny -0.86675
531
## dispositionjoint                                  dispositionjoint -0.09722
306
## facetyperobot:dispositionjoint      facetyperobot:dispositionjoint  0.32064
183
## facetypeuncanny:dispositionjoint facetypeuncanny:dispositionjoint  0.02366
752
##                                   Std..Error
```

```
## (Intercept)                        0.08091208
## facetyperobot                      0.02249371
## facetypeuncanny                    0.02243258
## dispositionjoint                   0.02241480
## facetyperobot:dispositionjoint     0.03174879
## facetypeuncanny:dispositionjoint   0.03172333
```

```
#confidence intervals
fixed_confint_like <- confint(model_like, level = 0.95)
```

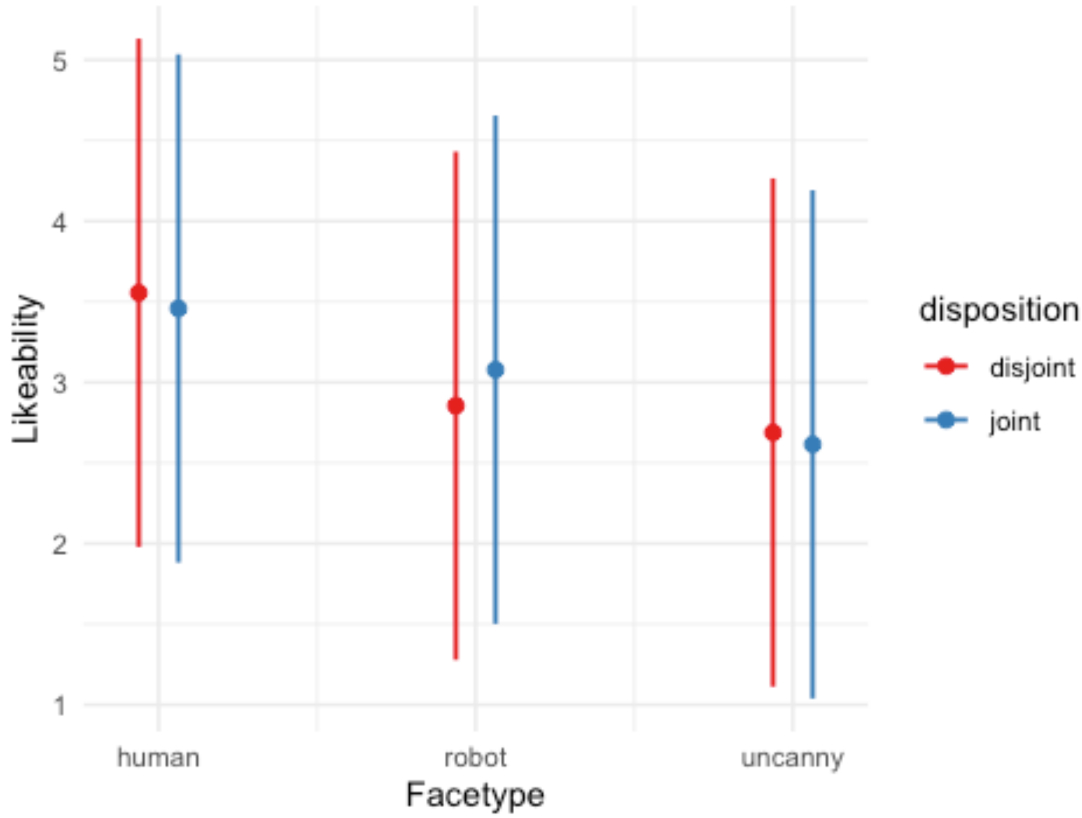
```
## Computing profile confidence intervals ...
```

```
print(fixed_confint_like)
```

```
##                                         2.5 %      97.5 %
## .sig01                             0.37151020  0.59716087
## .sigma                             0.79125153  0.80923167
## (Intercept)                        3.39504066  3.71602666
## facetyperobot                     -0.74489872 -0.65673393
## facetypeuncanny                   -0.91071872 -0.82279351
## dispositionjoint                  -0.14115113 -0.05329565
## facetyperobot:dispositionjoint     0.25842315  0.38286355
## facetypeuncanny:dispositionjoint  -0.03850341  0.08583718
```

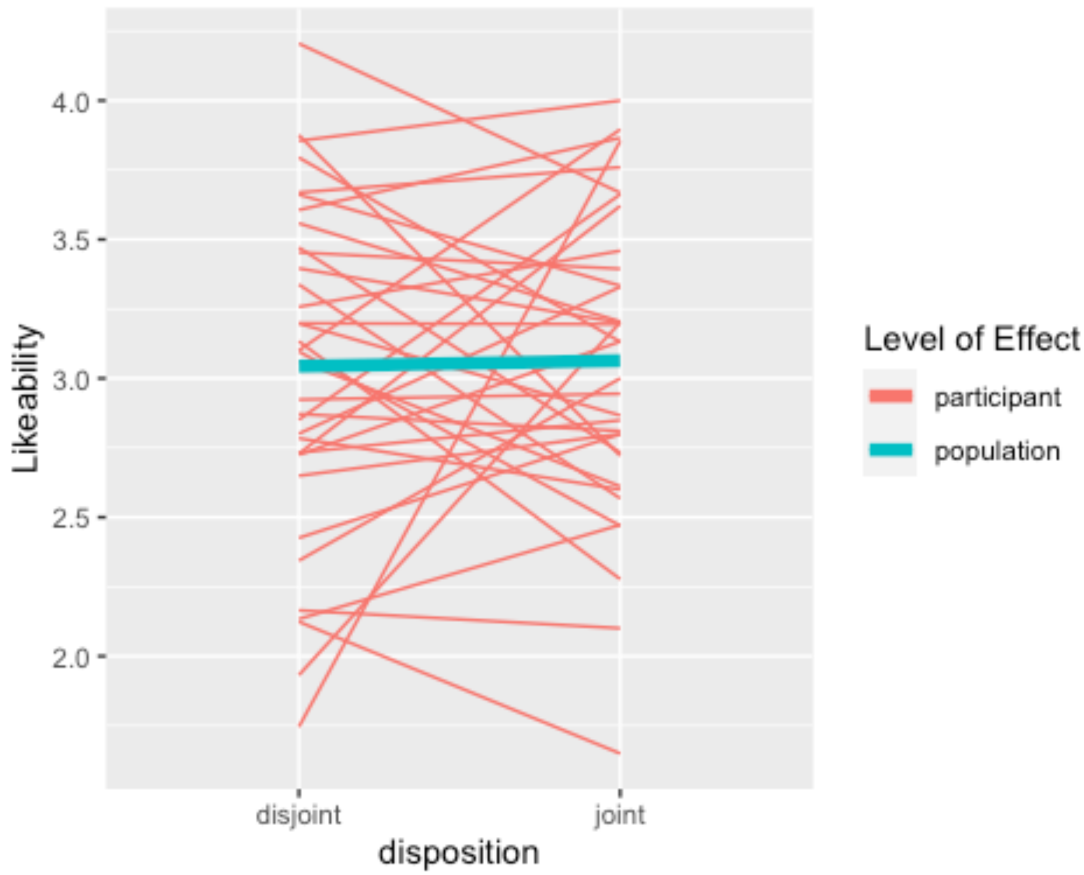
Plot model likeability

```
ggpredict(model_like, terms = c("facetype", "disposition"), type = "re") %>%
   plot() +
   labs(x = "Facetype", y = "Likeability", title = "") +
   theme_minimal()
```

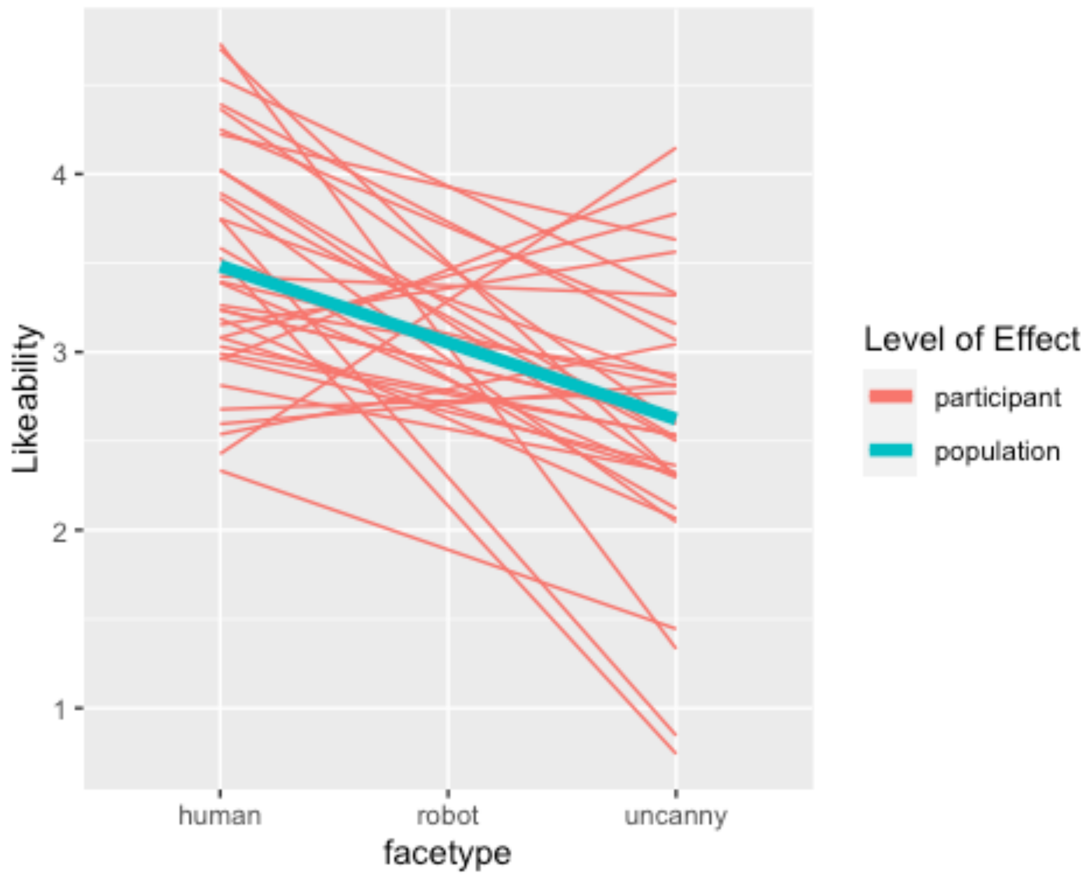


Universality likeability

```
#plot for disposition
everything_data %>%
  ggplot(aes(
    x = disposition,
    y = Likeability,
    group = participant
  )) +
  geom_smooth(aes(color = "participant"),
    size = .5, se = F, method = "lm"
  ) +
  geom_smooth(aes(group = 1, color = "population"),
    size = 2, se = F, method = "lm"
  ) +
  labs(color = "Level of Effect")

## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```




```
#plot for facetype
everything_data %>%
  ggplot(aes(
    x = facetype,
    y = Likeability,
    group = participant
  )) +
  geom_smooth(aes(color = "participant"),
    size = .5, se = F, method = "lm"
  ) +
  geom_smooth(aes(group = 1, color = "population"),
    size = 2, se = F, method = "lm"
  ) +
  labs(color = "Level of Effect")

## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```



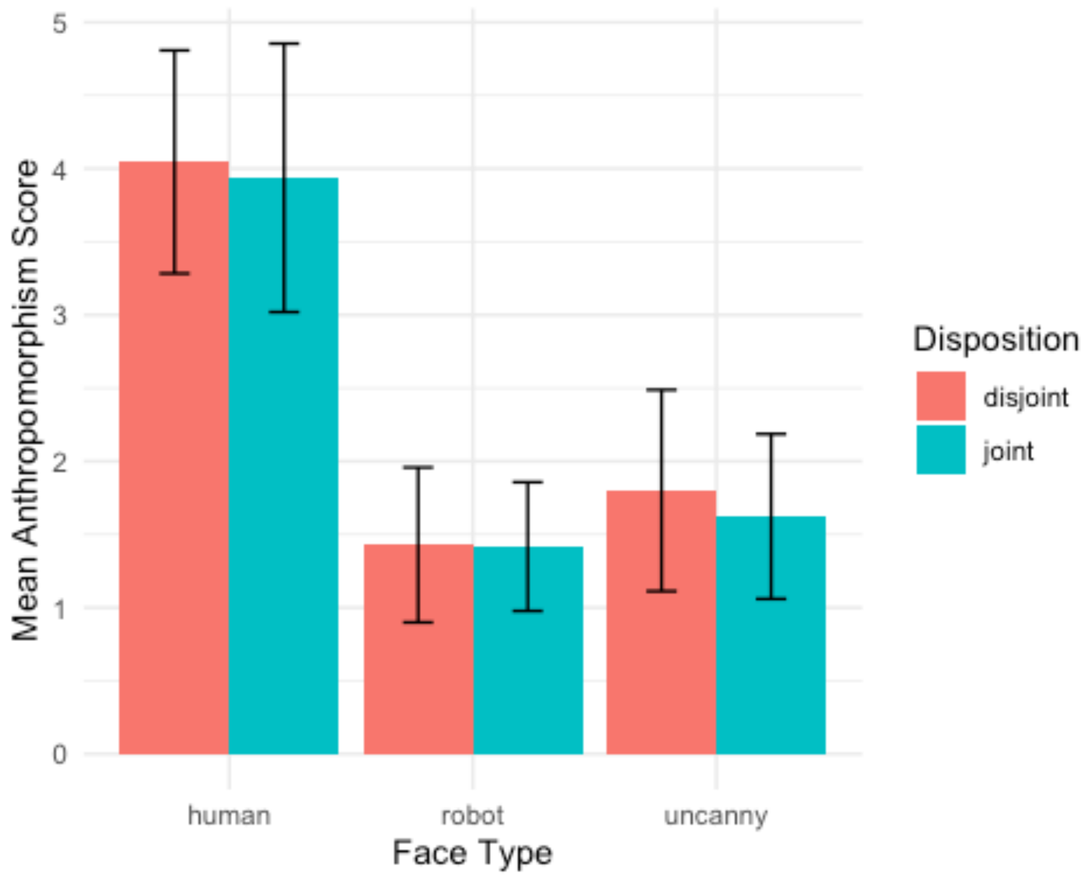
Anthropomorphism

```
#same as with likeability, getting only one score per face per participant
anthrograph <- everything_data %>%
  select(participant,facetype, disposition, Anthropomorphism) %>%
  group_by(facetype)

anthrograph <- anthrograph %>%
  distinct()

print(anthrograph)

## # A tibble: 210 × 4
## # Groups:   facetype [3]
##    participant facetype disposition Anthropomorphism
##          <dbl> <chr>    <chr>                  <dbl>
##  1         201 human    joint                    3.4
##  2         201 robot    disjoint                 1.4
##  3         201 uncanny  joint                    1.6
##  4         201 robot    joint                    1.2
##  5         201 uncanny  disjoint                 1.6
##  6         201 human    disjoint                 2.4
##  7         202 human    joint                    3.2
```

```
## 8          202 robot    joint                     2
## 9          202 uncanny  joint                     2.2
## 10         202 robot    disjoint                  1.4
## # ℹ 200 more rows
```

Plot avg anthropomorphism

```
# Calculate mean and standard deviation for Likeability by facetype and dispo
sition
anthrograph_summary <- anthrograph %>%
  group_by(facetype, disposition) %>%
  summarise(mean_anthro = mean(Anthropomorphism),
            sd_anthro = sd(Anthropomorphism))

## `summarise()` has grouped output by 'facetype'. You can override using the
## `.groups` argument.

#bar plot with error bars
ggplot(anthrograph_summary, aes(x = facetype, y = mean_anthro, fill = disposi
tion)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_errorbar(aes(ymin = mean_anthro - sd_anthro, ymax = mean_anthro + sd_a
nthro),
                position = position_dodge(width = 0.9), width = 0.25) +
  labs(x = "Face Type", y = "Mean Anthropomorphism Score", fill = "Dispositio
n") +
  theme_minimal()
```



LMM anthropomorphism

```
model_anthro <- lmer(Anthropomorphism ~ facetype * disposition + (1 | partici
pant),
                data = everything_data)
summary(model_anthro)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Anthropomorphism ~ facetype * disposition + (1 | participant)
##    Data: everything_data
##
## REML criterion at convergence: 24648.4
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.6543 -0.6554  0.0110  0.5884  2.9771
##
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  participant (Intercept) 0.1455   0.3815
##  Residual                0.2904   0.5389
## Number of obs: 15253, groups:  participant, 35
##
```

```
## Fixed effects:
##                                    Estimate Std. Error  t value
## (Intercept)                         4.04620    0.06537   61.900
## facetyperobot                      -2.61739    0.01515 -172.794
## facetypeuncanny                    -2.24644    0.01511 -148.709
## dispositionjoint                   -0.10466    0.01509   -6.934
## facetyperobot:dispositionjoint      0.08659    0.02138    4.050
## facetypeuncanny:dispositionjoint -0.07973    0.02136   -3.732
##
## Correlation of Fixed Effects:
##             (Intr) fctypr fctypn dspstn fctypr:
## facetyperbt -0.116
## factypncnny -0.116  0.501
## dispostnjnt -0.116  0.501  0.502
## fctyprbt:ds  0.082 -0.708 -0.355 -0.706
## fctypncnny:  0.082 -0.354 -0.707 -0.707  0.499
```

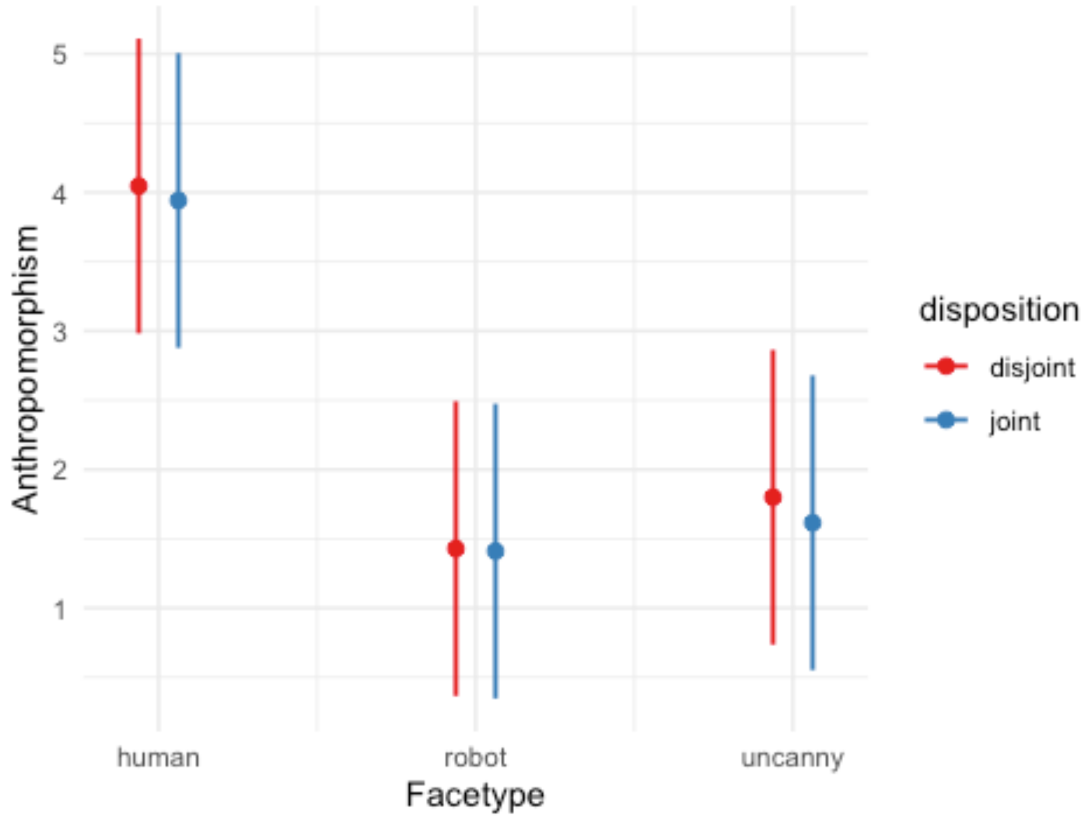
Results model anthropomorphism

```
summary_fixed_anthro <- summary(model_anthro)$coefficients

# Extract fixed effects estimates
fixed_effects_estimates_anthro <- summary_fixed_anthro[, "Estimate"]

# Extract standard errors
standard_errors_anthro <- summary_fixed_anthro[, "Std. Error"]


# Create a data frame for reporting
fixed_effects_table_anthro <- data.frame(
  Fixed_Effects = rownames(summary_fixed_anthro),
  Estimate = fixed_effects_estimates_anthro,
  `Std. Error` = standard_errors_anthro
)

print(fixed_effects_table_anthro)

##                                                     Fixed_Effects    Estim
ate
## (Intercept)                                           (Intercept)  4.04620
492
## facetyperobot                                       facetyperobot -2.61738
585
## facetypeuncanny                                   facetypeuncanny -2.24643
842
## dispositionjoint                                 dispositionjoint -0.10466
398
## facetyperobot:dispositionjoint     facetyperobot:dispositionjoint  0.08658
898
## facetypeuncanny:dispositionjoint facetypeuncanny:dispositionjoint -0.07972
```

```
875
##                                   Std..Error
## (Intercept)                       0.06536711
## facetyperobot                     0.01514747
## facetypeuncanny                   0.01510631
## dispositionjoint                  0.01509433
## facetyperobot:dispositionjoint    0.02137993
## facetypeuncanny:dispositionjoint  0.02136278

#confidence intervals
fixed_confint_anthro <- confint(model_anthro, level = 0.95)

## Computing profile confidence intervals ...

print(fixed_confint_anthro)

##                                        2.5 %      97.5 %
## .sig01                            0.30215930  0.48518613
## .sigma                            0.53283595  0.54494395
## (Intercept)                       3.91649399  4.17590777
## facetyperobot                    -2.64707183 -2.58770085
## facetypeuncanny                  -2.27604373 -2.21683408
## dispositionjoint                 -0.13424503 -0.07508233
## facetyperobot:dispositionjoint    0.04469002  0.12848932
## facetypeuncanny:dispositionjoint -0.12159498 -0.03786289
```

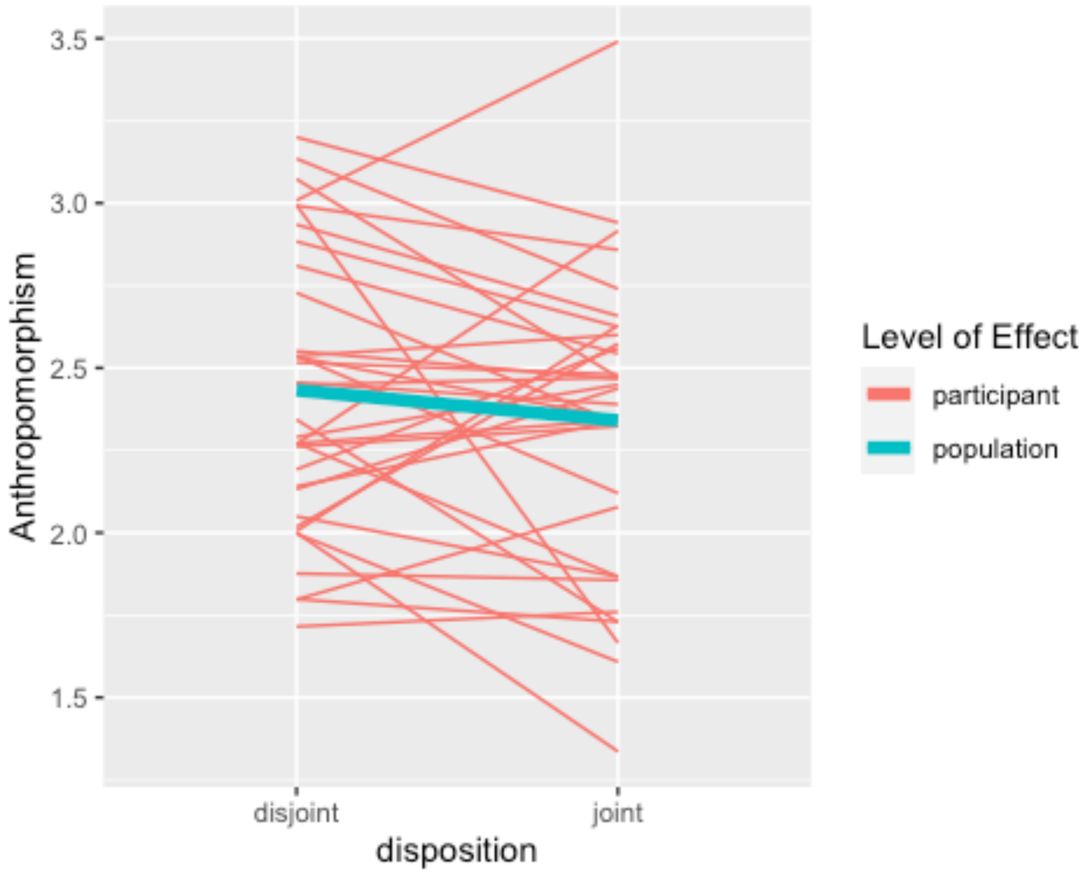
Plot model anthropomorphism

```
ggpredict(model_anthro, terms = c("facetype", "disposition"), type = "re") %>%
%
   plot() +
   labs(x = "Facetype", y = "Anthropomorphism", title = "") +
   theme_minimal()
```

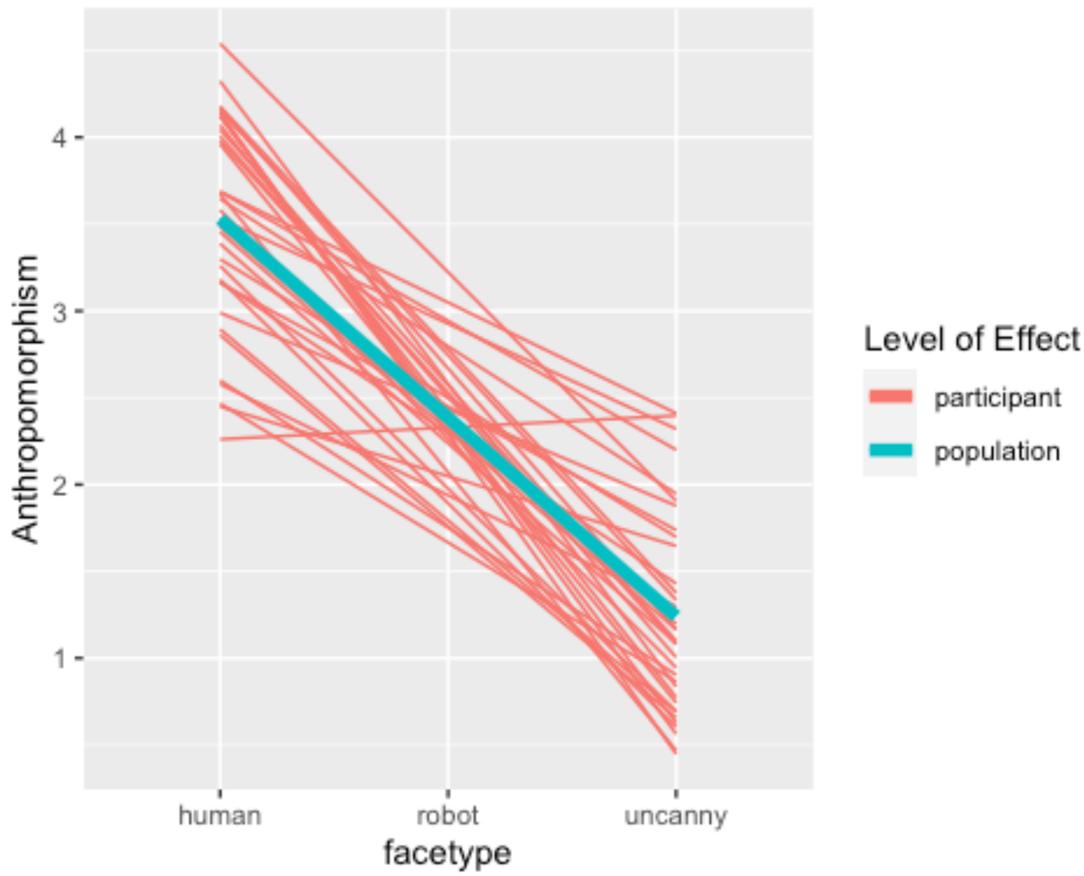


Universality anthropomorphism

```
#plot for disposition
everything_data %>%
  ggplot(aes(
    x = disposition,
    y = Anthropomorphism,
    group = participant
  )) +
  geom_smooth(aes(color = "participant"),
    size = .5, se = F, method = "lm"
  ) +
  geom_smooth(aes(group = 1, color = "population"),
    size = 2, se = F, method = "lm"
  ) +
  labs(color = "Level of Effect")

## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```




```
#plot for facetype
everything_data %>%
  ggplot(aes(
    x = facetype,
    y = Anthropomorphism,
    group = participant
  )) +
  geom_smooth(aes(color = "participant"),
    size = .5, se = F, method = "lm"
  ) +
  geom_smooth(aes(group = 1, color = "population"),
    size = 2, se = F, method = "lm"
  ) +
  labs(color = "Level of Effect")

## `geom_smooth()` using formula = 'y ~ x'
## `geom_smooth()` using formula = 'y ~ x'
```



Additional analyses

Looking at only first half

```
#creating new dataset for only the first half of the experiment
firsthalfdata <- combined_data %>%
  filter(half == "first_half")
```

Modelling only first half

```
model_firsthalf <- lmer(RT ~ Following * disposition * facetype + (1 | partic
ipant), data = firsthalfdata)
summary(model_firsthalf)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: RT ~ Following * disposition * facetype + (1 | participant)
##    Data: firsthalfdata
##
## REML criterion at convergence: 103481.5
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3857 -0.6554 -0.2171  0.4092  5.7384
```

```
##
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  participant (Intercept) 30173    173.7
##  Residual                52638    229.4
## Number of obs: 7543, groups:  participant, 35
##
## Fixed effects:
##                                                       Estimate Std. Error
## (Intercept)                                             854.41      32.64
## Followingunfollowed                                     -16.80      15.99
## dispositionjoint                                        -19.35      16.01
## facetyperobot                                           -24.47      20.04
## facetypeuncanny                                         -24.55      20.26
## Followingunfollowed:dispositionjoint                     20.70      22.94
## Followingunfollowed:facetyperobot                        35.51      22.50
## Followingunfollowed:facetypeuncanny                      21.36      22.73
## dispositionjoint:facetyperobot                           27.22      22.52
## dispositionjoint:facetypeuncanny                         21.17      22.71
## Followingunfollowed:dispositionjoint:facetyperobot      -40.49      32.05
## Followingunfollowed:dispositionjoint:facetypeuncanny    -40.39      32.55
##                                                       t value
## (Intercept)                                            26.179
## Followingunfollowed                                    -1.050
## dispositionjoint                                       -1.209
## facetyperobot                                          -1.221
## facetypeuncanny                                        -1.212
## Followingunfollowed:dispositionjoint                    0.903
## Followingunfollowed:facetyperobot                       1.578
## Followingunfollowed:facetypeuncanny                     0.940
## dispositionjoint:facetyperobot                          1.209
## dispositionjoint:facetypeuncanny                        0.932
## Followingunfollowed:dispositionjoint:facetyperobot     -1.264
## Followingunfollowed:dispositionjoint:facetypeuncanny   -1.241
##
## Correlation of Fixed Effects:
##                                (Intr) Fllwng dspstn fctypr fctypn Fllwngnfl
lwd:d
## Fllwngnfllw                    -0.389
## dispostnjnt                    -0.389  0.792
## facetyperbt                    -0.310  0.633  0.633
## factypncnny                    -0.307  0.626  0.625  0.499
## Fllwngnfllwd:d                  0.271 -0.697 -0.698 -0.441 -0.436
## Fllwngnfllwd:fctypr             0.276 -0.711 -0.563 -0.890 -0.445  0.496
## Fllwngnfllwd:fctypn             0.273 -0.704 -0.557 -0.445 -0.892  0.491
## dspstnjnt:fctypr                0.276 -0.564 -0.711 -0.890 -0.444  0.496
## dspstnjnt:fctypn                0.274 -0.558 -0.704 -0.445 -0.892  0.492
## Fllwngnfllwd:dspstnjnt:fctypr  -0.194  0.499  0.499  0.625  0.312 -0.716
## Fllwngnfllwd:dspstnjnt:fctypn  -0.191  0.491  0.491  0.311  0.622 -0.705
##                                Fllwngnfllwd:fctypr Fllwngnfllwd:fctypn
```

```
## Fllwngnfllw
## dispostnjnt
## facetyperbt
## factypncnny
## Fllwngnfllwd:d
## Fllwngnfllwd:fctypr
## Fllwngnfllwd:fctypn            0.500
## dspstnjnt:fctypr               0.792               0.396
## dspstnjnt:fctypn               0.397               0.795
## Fllwngnfllwd:dspstnjnt:fctypr -0.702              -0.351
## Fllwngnfllwd:dspstnjnt:fctypn -0.349              -0.698
##                               dspstnjnt:fctypr dspstnjnt:fctypn
## Fllwngnfllw
## dispostnjnt
## facetyperbt
## factypncnny
## Fllwngnfllwd:d
## Fllwngnfllwd:fctypr
## Fllwngnfllwd:fctypn
## dspstnjnt:fctypr
## dspstnjnt:fctypn               0.500
## Fllwngnfllwd:dspstnjnt:fctypr -0.702           -0.351
## Fllwngnfllwd:dspstnjnt:fctypn -0.349           -0.698
##                               Fllwngnfllwd:dspstnjnt:fctypr
## Fllwngnfllw
## dispostnjnt
## facetyperbt
## factypncnny
## Fllwngnfllwd:d
## Fllwngnfllwd:fctypr
## Fllwngnfllwd:fctypn
## dspstnjnt:fctypr
## dspstnjnt:fctypn
## Fllwngnfllwd:dspstnjnt:fctypr
## Fllwngnfllwd:dspstnjnt:fctypn  0.504
```

Results of model first half

```
summary_fixed <- summary(model_firsthalf)$coefficients

#fixed effects
fixed_effects_estimates_first <- summary_fixed[, "Estimate"]

#SEs
standard_errors_first <- summary_fixed[, "Std. Error"]

#data frame
fixed_effects_table_first <- data.frame(
  Fixed_Effects = rownames(summary_fixed),
  Estimate = fixed_effects_estimates_first,
```

```
  `Std. Error` = standard_errors_first
)
print(fixed_effects_table_first)

##
Fixed_Effects
## (Intercept)
(Intercept)
## Followingunfollowed
Followingunfollowed
## dispositionjoint
dispositionjoint
## facetyperobot
facetyperobot
## facetypeuncanny
facetypeuncanny
## Followingunfollowed:dispositionjoint                                 Follo
wingunfollowed:dispositionjoint
## Followingunfollowed:facetyperobot                                       Fo
llowingunfollowed:facetyperobot
## Followingunfollowed:facetypeuncanny                                   Foll
owingunfollowed:facetypeuncanny
## dispositionjoint:facetyperobot
dispositionjoint:facetyperobot
## dispositionjoint:facetypeuncanny                                         d
ispositionjoint:facetypeuncanny
## Followingunfollowed:dispositionjoint:facetyperobot     Followingunfollowed
:dispositionjoint:facetyperobot
## Followingunfollowed:dispositionjoint:facetypeuncanny Followingunfollowed:d
ispositionjoint:facetypeuncanny
##                                                       Estimate Std..Error
## (Intercept)                                          854.40784   32.63661
## Followingunfollowed                                  -16.79872   15.99499
## dispositionjoint                                     -19.34773   16.00840
## facetyperobot                                        -24.46927   20.03533
## facetypeuncanny                                      -24.55425   20.26031
## Followingunfollowed:dispositionjoint                  20.70355   22.93937
## Followingunfollowed:facetyperobot                     35.51378   22.49936
## Followingunfollowed:facetypeuncanny                   21.36330   22.72653
## dispositionjoint:facetyperobot                        27.22258   22.51580
## dispositionjoint:facetypeuncanny                      21.16521   22.71452
## Followingunfollowed:dispositionjoint:facetyperobot   -40.49207   32.04682
## Followingunfollowed:dispositionjoint:facetypeuncanny -40.39338   32.54670

#confidence intervals
fixed_confint_first <- confint(model_firsthalf, level = 0.95)

## Computing profile confidence intervals ...

print(fixed_confint_first)
```

```
##                                                           2.5 %    97.5 %
## .sig01                                               137.439719 221.06343
## .sigma                                               225.642070 232.97704
## (Intercept)                                          790.005460 918.79448
## Followingunfollowed                                  -48.131917  14.52940
## dispositionjoint                                     -50.707442  12.00641
## facetyperobot                                        -63.716411  14.77314
## facetypeuncanny                                      -64.240386  15.13051
## Followingunfollowed:dispositionjoint                 -24.224749  65.64166
## Followingunfollowed:facetyperobot                     -8.554475  79.58808
## Followingunfollowed:facetypeuncanny                  -23.152750  65.87969
## dispositionjoint:facetyperobot                       -16.877541  71.32941
## dispositionjoint:facetypeuncanny                     -23.326691  65.65870
## Followingunfollowed:dispositionjoint:facetyperobot  -103.268131  22.27711
## Followingunfollowed:dispositionjoint:facetypeuncanny -104.147138  23.35636
```

Looking at likeability and anthropomorphism scores by list and per face

```
# Group by 'list' and calculate averages for each column
averages_by_list <- psychopy_qualtrics %>%
  group_by(list) %>%
  summarise(
    human1_avg_anthro_avg = mean(human1_avg_anthro, na.rm = TRUE),
    human1_avg_like_avg = mean(human1_avg_like, na.rm = TRUE),
    human2_avg_anthro_avg = mean(human2_avg_anthro, na.rm = TRUE),
    human2_avg_like_avg = mean(human2_avg_like, na.rm = TRUE),
    robot1_avg_anthro_avg = mean(robot1_avg_anthro, na.rm = TRUE),
    robot1_avg_like_avg = mean(robot1_avg_like, na.rm = TRUE),
    robot2_avg_anthro_avg = mean(robot2_avg_anthro, na.rm = TRUE),
    robot2_avg_like_avg = mean(robot2_avg_like, na.rm = TRUE),
    uncanny1_avg_anthro_avg = mean(uncanny1_avg_anthro, na.rm = TRUE),
    uncanny1_avg_like_avg = mean(uncanny1_avg_like, na.rm = TRUE),
    uncanny2_avg_anthro_avg = mean(uncanny2_avg_anthro, na.rm = TRUE),
    uncanny2_avg_like_avg = mean(uncanny2_avg_like, na.rm = TRUE)
  )

head(averages_by_list)

## # A tibble: 2 × 13
##    list human1_avg_anthro_avg human1_avg_like_avg human2_avg_anthro_avg
##   <dbl>                 <dbl>               <dbl>                 <dbl>
## 1     1                  3.81                3.71                  3.97
## 2     2                  4.14                3.69                  4.08
## # ℹ 9 more variables: human2_avg_like_avg <dbl>, robot1_avg_anthro_avg <d
bl>,
## #   robot1_avg_like_avg <dbl>, robot2_avg_anthro_avg <dbl>,
## #   robot2_avg_like_avg <dbl>, uncanny1_avg_anthro_avg <dbl>,
## #   uncanny1_avg_like_avg <dbl>, uncanny2_avg_anthro_avg <dbl>,
## #   uncanny2_avg_like_avg <dbl>
```

```r
#not grouped by list, just avg per face
averages_anthro_like <- psychopy_qualtrics %>%
  summarise(
    human1_avg_anthro_avg = mean(human1_avg_anthro, na.rm = TRUE),
    human1_avg_like_avg = mean(human1_avg_like, na.rm = TRUE),
    human2_avg_anthro_avg = mean(human2_avg_anthro, na.rm = TRUE),
    human2_avg_like_avg = mean(human2_avg_like, na.rm = TRUE),
    robot1_avg_anthro_avg = mean(robot1_avg_anthro, na.rm = TRUE),
    robot1_avg_like_avg = mean(robot1_avg_like, na.rm = TRUE),
    robot2_avg_anthro_avg = mean(robot2_avg_anthro, na.rm = TRUE),
    robot2_avg_like_avg = mean(robot2_avg_like, na.rm = TRUE),
    uncanny1_avg_anthro_avg = mean(uncanny1_avg_anthro, na.rm = TRUE),
    uncanny1_avg_like_avg = mean(uncanny1_avg_like, na.rm = TRUE),
    uncanny2_avg_anthro_avg = mean(uncanny2_avg_anthro, na.rm = TRUE),
    uncanny2_avg_like_avg = mean(uncanny2_avg_like, na.rm = TRUE)
  )

head(averages_anthro_like)
```

```
##   human1_avg_anthro_avg human1_avg_like_avg human2_avg_anthro_avg
## 1              3.983007            3.701606              4.027011
##   human2_avg_like_avg robot1_avg_anthro_avg robot1_avg_like_avg
## 1            3.342385              1.310155            2.875579
##   robot2_avg_anthro_avg robot2_avg_like_avg uncanny1_avg_anthro_avg
## 1              1.548154            3.085609                1.645237
##   uncanny1_avg_like_avg uncanny2_avg_anthro_avg uncanny2_avg_like_avg
## 1              2.134269                1.797456              3.201718
```

Looking at avg likeability and anthropomorphism per disposition

```r
averages_by_dispo <- psychopy_qualtrics %>%
  group_by(disposition) %>%
  summarise(
    human1_avg_anthro_avg = mean(human1_avg_anthro, na.rm = TRUE),
    human1_avg_like_avg = mean(human1_avg_like, na.rm = TRUE),
    human2_avg_anthro_avg = mean(human2_avg_anthro, na.rm = TRUE),
    human2_avg_like_avg = mean(human2_avg_like, na.rm = TRUE),
    robot1_avg_anthro_avg = mean(robot1_avg_anthro, na.rm = TRUE),
    robot1_avg_like_avg = mean(robot1_avg_like, na.rm = TRUE),
    robot2_avg_anthro_avg = mean(robot2_avg_anthro, na.rm = TRUE),
    robot2_avg_like_avg = mean(robot2_avg_like, na.rm = TRUE),
    uncanny1_avg_anthro_avg = mean(uncanny1_avg_anthro, na.rm = TRUE),
    uncanny1_avg_like_avg = mean(uncanny1_avg_like, na.rm = TRUE),
    uncanny2_avg_anthro_avg = mean(uncanny2_avg_anthro, na.rm = TRUE),
    uncanny2_avg_like_avg = mean(uncanny2_avg_like, na.rm = TRUE)
  )
print(averages_by_dispo)
```

```
## # A tibble: 2 × 13
##   disposition human1_avg_anthro_avg human1_avg_like_avg human2_avg_anthro_
```

```
avg
##   <chr>                            <dbl>               <dbl>                 <d
bl>
## 1 disjoint                          3.98                3.70                  4
.02
## 2 joint                             3.99                3.70                  4
.03
## # ℹ 9 more variables: human2_avg_like_avg <dbl>, robot1_avg_anthro_avg <d
bl>,
## #   robot1_avg_like_avg <dbl>, robot2_avg_anthro_avg <dbl>,
## #   robot2_avg_like_avg <dbl>, uncanny1_avg_anthro_avg <dbl>,
## #   uncanny1_avg_like_avg <dbl>, uncanny2_avg_anthro_avg <dbl>,
## #   uncanny2_avg_like_avg <dbl>
```

Looking at likeability per list (per face)

```
#looking at just likeability
average_likeability <- everything_data %>%
  group_by(list) %>%
  summarise(
    human1_avg_like_avg = mean(human1_avg_like, na.rm = TRUE),
    human2_avg_like_avg = mean(human2_avg_like, na.rm = TRUE),
    robot1_avg_like_avg = mean(robot1_avg_like, na.rm = TRUE),
    robot2_avg_like_avg = mean(robot2_avg_like, na.rm = TRUE),
    uncanny1_avg_like_avg = mean(uncanny1_avg_like, na.rm = TRUE),
    uncanny2_avg_like_avg = mean(uncanny2_avg_like, na.rm = TRUE)
  )

print(average_likeability)

## # A tibble: 2 × 7
##    list human1_avg_like_avg human2_avg_like_avg robot1_avg_like_avg
##   <dbl>               <dbl>               <dbl>               <dbl>
## 1     1                3.71                3.44                2.91
## 2     2                3.69                3.26                2.84
## # ℹ 3 more variables: robot2_avg_like_avg <dbl>, uncanny1_avg_like_avg <d
bl>,
## #   uncanny2_avg_like_avg <dbl>
```

Looking at median per disposition

```
median_by_dispo <- psychopy_qualtrics %>%
  group_by(disposition) %>%
  summarise(
    human1_avg_anthro_avg = median(human1_avg_anthro, na.rm = TRUE),
    human1_avg_like_avg = median(human1_avg_like, na.rm = TRUE),
    human2_avg_anthro_avg = median(human2_avg_anthro, na.rm = TRUE),
    human2_avg_like_avg = median(human2_avg_like, na.rm = TRUE),
    robot1_avg_anthro_avg = median(robot1_avg_anthro, na.rm = TRUE),
    robot1_avg_like_avg = median(robot1_avg_like, na.rm = TRUE),
```

```
    robot2_avg_anthro_avg = median(robot2_avg_anthro, na.rm = TRUE),
    robot2_avg_like_avg = median(robot2_avg_like, na.rm = TRUE),
    uncanny1_avg_anthro_avg = median(uncanny1_avg_anthro, na.rm = TRUE),
    uncanny1_avg_like_avg = median(uncanny1_avg_like, na.rm = TRUE),
    uncanny2_avg_anthro_avg = median(uncanny2_avg_anthro, na.rm = TRUE),
    uncanny2_avg_like_avg = median(uncanny2_avg_like, na.rm = TRUE)
  )
print(median_by_dispo)

## # A tibble: 2 × 13
##   disposition human1_avg_anthro_avg human1_avg_like_avg human2_avg_anthro_
avg
##   <chr>                       <dbl>               <dbl>                <d
bl>
## 1 disjoint                        4                 3.8
4
## 2 joint                           4                 3.8
4
## # ℹ 9 more variables: human2_avg_like_avg <dbl>, robot1_avg_anthro_avg <d
bl>,
## #   robot1_avg_like_avg <dbl>, robot2_avg_anthro_avg <dbl>,
## #   robot2_avg_like_avg <dbl>, uncanny1_avg_anthro_avg <dbl>,
## #   uncanny1_avg_like_avg <dbl>, uncanny2_avg_anthro_avg <dbl>,
## #   uncanny2_avg_like_avg <dbl>
```