From Robots to Primates:
Tracing the Uncanny Valley Effect to its Evolutionary Origin

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Contents

Abstract

Despite years of research and an abundance of theoretical approaches, the underpinnings of the uncanny valley effect still remain a mystery. Recent research has argued that the negative appraisal of highly human-like entities is the result of fast-processing systems, rather than of slow, deliberate cognitive efforts. To shine light on its origin, we detach the uncanny valley effect from the field of robotics and investigate it from an evolutionary-psychological perspective with use of biological stimuli. In an online experiment, participants viewed and rated a range of primate and robot faces on eeriness and likeability. We introduced the concept of ancestral closeness as an objective measure for human-likeness. We were overall able to replicate the uncanny valley effect using primate faces and found it is highly likely to be experienced by every participant. Thereby, we support the involvement of evolved, fast-processing systems in bringing about the uncanny valley effect and argue against theories of realism inconsistency and traditional category uncertainty. Surprisingly, the stimuli falling into the uncanny valley had a visibly white sclera which we argue to be an evolved feature most distinctly displayed in homo sapiens. We conclude that the uncanny valley effect is a mechanism evolved under the selection pressure that benefits intraspecies communication, reproductive fitness and ultimately, self-preservation. These findings allow us to detach the phenomenon from its original context and pave the way for future research to unravel its evolutionary advantages.

Keywords: uncanny valley, evolutionary origin, human ancestors, primates, face prototype

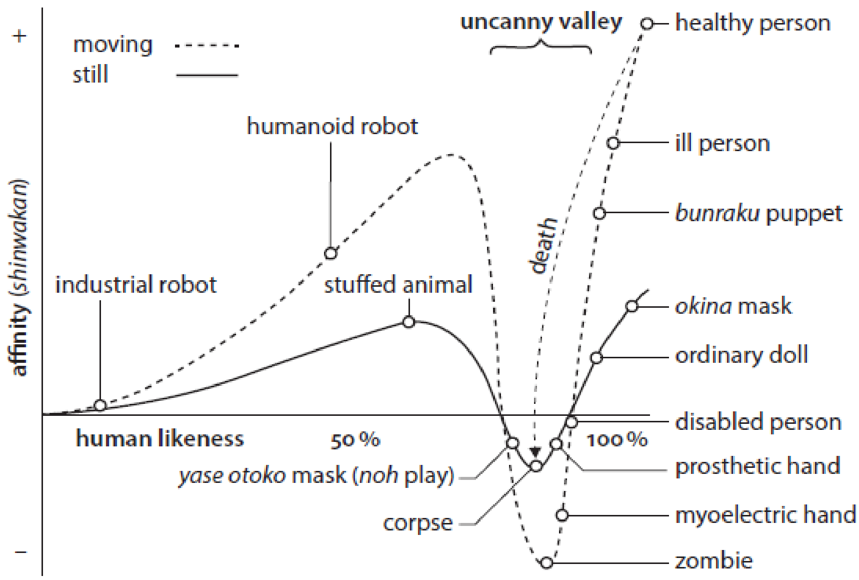
Introduction

In recent years, there has been an increasing demand to successfully create enjoyable and highly realistic human-like agents for the game and movie industry as well as for social interaction. However, instead of being enjoyable, humanoid characters in productions such as “The Polar Express” (Zemeckis, 2005), “A Christmas Carol” (West, 2009) and “Final Fantasy: The Spirits Within” (Sakaguchi & Aida, 2001) have left their audiences rather horrified. The viewers were unable to identify with the characters as they are repelled by their ‘soulless’ appearance (MacDorman & Chattopadhyay, 2016). Ultimately, the characters’ rather high human-likeness poses a threat to movie productions’ success and can lead to the studio shutting down, e.g. in the case of ImageMovers Digital (Tinwell, 2014; MacDorman & Entezari, 2015). The domain of human-robot interaction has encountered comparable problems as feelings of aversion towards robots and androids hinder the process of interacting (MacDorman & Ishiguro, 2006). The phenomenon eliciting these problems is called the uncanny valley effect and describes the negative emotional response evoked by a nearly human-like entity.

The uncanny valley effect was first proposed by Japanese roboticist Mori in 1970. Based on his own observations and feelings, Mori suggested a graph depicting the relationship between an entity’s human-likeness and its affinity (see Figure 1), or also called likeability. Accordingly, the likeability towards robots grows as human-likeness increases. However, entities of moderate to high human-likeness evoke feelings of eeriness which result in a negative emotional response, or low likeability (Mori et al., 2012). This drop in the otherwise positive curve is what constitutes the uncanny valley (MacDorman & Chattopadhyay, 2016). Ultimately, the valley is followed by a sharp final increase in likeability when human-likeness increases further. This response appears to be independent of whether or not an individual is commonly exposed to robots, thereby indicating a robustness of the uncanny valley effect (Alvarez Perez et al., 2020).

Figure 1

The Dashed Line Representing the Uncanny Valley as Proposed by Mori (1970/2012)



Note. From “Individual differences predict sensitivity to the uncanny valley” by K. F. MacDorman and S. O. Entezari, 2015, Interaction Studies. *Social Behaviour and Communication in Biological and Artificial Systems, 16*(2), p. 142. Copyright [2015] by John Benjamins Publishing Company.

Mori hypothetically proposed the uncanny valley effect for robots and prosthetics more than 50 years ago. Since then, it has also been observed for androids (MacDorman & Entezari, 2015; MacDorman & Ishiguro, 2006; Mathur & Reichling, 2016) and computer generated (CG) characters (MacDorman et al., 2009; Burleigh et al., 2013; Seyama & Nagayama, 2007; Tinwell, et al., 2011). ”Despite the decades-long prominence of the uncanny valley theory and robot designers’ sophisticated attempts to circumvent it” (Mathur et al., 2020, p. 29), a full understanding of the uncanny valley has yet to be accomplished. Consequently, researchers have advised to avoid highly realistic entities. Because of that producers have opted for more unrealistic characters instead (Canemaker, 2004). Different aspects can make a robot or CG character more appealing and thus, less uncanny. For instance, if they exhibit less emotionality (Kim et al., 2019) and have a more traditional, cartoonish style with a simplified animation and exaggerated features (Kätsyri et al., 2017). As demonstrated in a study by Kim et al. (2019), the less human-like consumer robots elicited less uncanny feelings than the highly human-like ones. However, as robots and humanoid agents play an increasingly important role in our contemporary society, it remains a challenge to make those generally likeable so they can be successfully implemented in human-robot interactions as well as movies and games (Haeske & Schmettow, 2016; Hinds et al., 2004). Therefore, unraveling the underlying mechanisms and the origins of the uncanny valley effect remains an important task.

Interestingly, the phenomenon has almost exclusively been studied in the context of robotics and computer graphics. Mori et al. (2012) suggest that "through robotics research, we can begin to understand what makes us human" (p. 100). A majority of the conducted studies build on the notion of cognitive responses which are more readily manipulable and quantifiable (Zhang et al., 2020). However, as researchers struggle to find an explanation within the field of robotics, it may be time to flip the approach and instead attempt to understand what made us human in the first place. Steckenfinger and Ghazanfar (2009) demonstrated the uncanny valley's presence in macaque monkeys, as the monkeys took more time looking at real and unrealistic synthetic faces than at realistic synthetic ones. This suggests that the uncanny valley effect, initially discovered for robots, may have its evolutionary origin in humans' phylogenetic development. Nevertheless, empirical evidence for theories from evolutionary psychology is lacking. To shine light on the phenomenon from an evolutionary psychological perspective, we examine whether the uncanny valley effect can be replicated using biological stimuli, rather than mechanical ones. By taking a step away from the field in which the uncanny valley effect is usually studied, we may gain more insight into what brought it about initially.

Face Processing

The majority of research on the uncanny valley effect has focused on the face rather than any other body part of robots and CG characters. Yu (2001) argues that the face is the most distinctive part of an individual's body as well as the focal point of human interaction. Its importance is further reflected in the finding that for judgments of overall physical attractiveness, facial attractiveness is more important than bodily attractiveness (Currie & Little, 2009). Thus, the face appears to be of primary importance for interaction and therefore, must also be involved in human-robot interaction. In the following, we consider the role of face processing for the uncanny valley effect.

Developmental Perspective

Empirical research shows that at birth, humans are equipped with a broad multisensory perceptual tuning that gets more specialised towards the end of the first year of life. This process is called perceptual narrowing (Lewkowicz & Ghazanfar, 2009). By reducing the range of information infants are sensitive to and sharpening their expertise for important features, they can focus on incorporating information that is socially relevant to them (Pascalis et al., 2005). As humans are highly frequently and selectively exposed to faces of other humans from early on, they develop a certain expertise for their conspecifics' faces, as opposed to those of other species (Pascalis et al., 2002; Simpson et al., 2011). The process of perceptual narrowing and the exposure to conspecifics results in the development of a general human face prototype.

Face Prototype

We can think of this face prototype as a compilation of acquired expertise about conspecifics' faces which is utilized when an individual encounters an entity. The more similar to the prototype a face is, the more sensitive the individual is to this face and the easier it is to distinguish it. However, the more the face deviates from the prototype, the less expertise the individual has about it, and hence, the less easy this face can be discriminated (Pascalis et al., 2005). Therefore, humans are more sensitive to highly human-like faces as opposed to less human-like ones (Looser & Wheatley, 2010). This expertise makes it easy for humans to detect negatively evaluated abnormalities in highly human-like robots and CG characters as those come close to the human face prototype. In line with this, researchers were able to observe the uncanny valley effect in infants of 12 months of age, but not in infants aged 6, 8, or 10 months (Lewkowicz & Ghazanfar, 2012). This finding demonstrates the necessity of a developed face prototype for the uncanny valley effect to emerge and is a crucial implication for how individuals may evaluate non-human primate faces.

The face prototype may entail information about facial features, such as eyes, mouth and nose, as well as about the features' unified 'Gestalt', called configuration. Both, featural and configurational information are important in face recognition (Cabeza & Kato, 2000). Among other features, the eyes contain a disproportionately great diagnostic value for indicating whether or not something is animate (Looser & Wheatley, 2010). Further, configural processing seems to have a special role for the processing of faces which match the prototype. Gothard et al. (as cited in Rádlová et al., 2018) found that monkeys use configural processing for categorising their conspecifics' faces but use featural processing for human faces. Humans, in turn, use configural processing only for human faces and mostly not for objects or non-human faces (Maurer et al., 2002; Tanaka & Gauthier, 1997). Furthermore, Hugenberg et al. (2016) found that configural processing affects the activation, categorization and ascription of humanness to a face. This might mean that the more human-like an entity is, the more likely configural processing is to be activated, and to categorise something as non-human, humans may rely more on feature-based processing.

Research shows that visual experience during the first few months of life is crucial to develop normal configural face processing (Le Grand et al., 2001). Thus, not only perceptual narrowing but also experiences with others are crucial for face processing to be established. A study by Feng et al. (2018) supports the importance of visual experience by demonstrating that children with Autism Spectrum Disorder (ASD) did not exhibit the uncanny valley effect, whereas typically developing children did. They proposed that the effect's absence in children with ASD could be accounted for by their decreased perceptual sensitivity to slight changes in facial features and the limited experience with faces due to a reduced social motivation. Hence, the development of a face prototype through perceptual narrowing and social experience is a crucial prerequisite for the uncanny valley effect. The absence of a human face prototype might make individuals immune against the uncanny valley effect, as it is the case for children with ASD.

These findings indicate the definite involvement of the human face prototype in, as well as its cruciality for, experiencing the uncanny valley effect. The face prototype is most sensitive for highly human-like entities which are therefore, more strictly evaluated than faces further away from the prototype. It might be that with increasing similarity to the face prototype configural, instead of featural, processing is utilized which makes the differences stand out. This in turn, may evoke a negative emotional response. In other words, the negative appraisal of highly humanoid robots and CG characters may be the result of an individual noticing even the slightest deviations from their human face prototype.

Explanations of the Uncanny Valley Effect

To understand the need for taking an evolutionary perspective on the uncanny valley effect, we examine already established explanations. MacDorman and Ishiguro (2006) called the uncanny valley effect a "hodgepodge of different phenomena" (p. 313) which is reflected in the abundance of different theories aiming to explain it. These can be structured into two approaches (Haeske & Schmettow, 2016). On the one hand, fast-system theories argue that the negative emotional response results from evolved automatic, specialized and stimulus-driven processing occurring early in perception (MacDorman et al., 2009). This means that the negative emotional response is said to come about automatically and without a deliberate evaluation of the encountered individual. On the other hand, slow system theories are based on broad, general and later occurring cognitive processing that involve conscious deliberation. Here, the negative appraisal of humanoid entities is said to be caused by cognitive conflicts (Zhang et al., 2020). Both systems are said to be involved simultaneously when human-like entities are being processed (MacDorman et al., 2009). However, whereas slow-processing approaches argue for individual differences, the fast-processing systems support the evolutionary perspective of the uncanny valley, whereas . In the following, the theories belonging to both systems will be elaborated on.

Slow Processing Theories

Categorical Uncertainty. In recent years, the categorical uncertainty hypothesis has been a prominent theory. Stimuli along the uncanny valley were said to be categorised as either belonging to the category human or non-human (Kätsyri et al., 2015). Accordingly, this theory argues that the negative emotional response to highly realistic faces emerges due to confusion about the categorization of a stimulus. The difficulty of assigning a stimulus to either category increases sharply at the category boundary to humanness, where researchers suggested the greatest categorization ambiguity (Cheetham et al., 2013; Mathur & Reichling, 2016). However, counter-evidence comes from an experiment using human and robot faces which found that the uncanny valley and the category boundary do not coincide (Marthur et al., 2020). In other words, maximally ambiguous faces were on average not disliked and so the category uncertainty theory was unable to explain the uncanny valley effect. Nevertheless, Mathur et al. (2020) still observed a categorization pattern, suggesting that humans do perceive a category boundary.

Realism Inconsistency. An alternative theory similar to category uncertainty draws on the notion of realism inconsistency (Mathur et al., 2020). Here, the negative emotional response towards a human-like face arises due to an inconsistent level of realism of the facial features (MacDorman & Chattopadhyay, 2016). For instance, a face can have highly realistic looking eyes but its skin texture may look cartoonish, thereby distorting the overall consistency of the features. Proponents of this theory argue that it is this difference in realism of for example the eyes and skin which brings about the negative emotional response. Making likeability a function of realism consistency, instead of human-likeness, would constitute a fundamental challenge to the conceptualization of the uncanny valley effect.

Violation of Expectation. As part of the slow processing theories, the violation of expectation hypothesis builds on cognitive processes involving conscious deliberation. This theory argues that an individual has subconscious human-directed expectations about how humans should look and behave in an interaction (MacDorman & Ishiguro, 2006). If, upon an encounter with a humanoid entity, these expectations are violated, the individual may experience an eerie sensation caused by the mismatch between expectations and reality (Mitchell et al., 2011). Thus, the uncanny valley effect might be the result of expectations arising from social interactions which are then violated and cause the negative emotional response.

Fast Processing Theories

Threat avoidance. The threat avoidance theory builds on an evolution-theoretical point of view. As suggested by Mori et al. (2012), the uncanny valley might be the result of humans' instinct for self-preservation. Over the course of evolution, the chances for self-preservation were heightened by avoiding threats, such as diseases, and increasing one's chances for successful reproduction. With increasing genetic similarity, the possibility of disease contraction rises (MacDorman et al., 2009). Thus, the more human-like something is, the more sensitive one is to its abnormalities (Green et al., 2008). The feelings of eeriness experienced when facing an imperfectly human-like entity may be the result of evolved mechanisms for pathogen avoidance, whereby imperfections are an indicator of disease or genetic defects (MacDorman et al., 2009). In line with this, Olivera-La Rosa (2018) has proposed that the negative emotional response acts as a protector from interaction with abnormal, and possibly threatening, individuals. This mechanism may have developed into an aversion towards any abnormalities of humanoid entities (MacDorman & Ishiguro, 2006). Therefore, the uncanny valley effect could be the result of evolutionary processes to increase chances of survival and reproductive success.

Evolutionary Aesthetics. Another mechanism for increasing reproductive success concerns the preferences in physical attractiveness. Attractiveness judgments are made automatically at a glance, remain stable over time, and have considerable agreement between individuals and cultures (Cunningham et al., 1995; Olson & Marshuetz, 2005; Willis & Todorov, 2006). These agreements on what is considered to be aesthetic are the result of the selection pressure in the course of evolution (MacDorman & Ishiguro, 2006; MacDorman et al., 2009). Preferences for averageness, bilateral symmetry, and skin quality are associated with health and fertility (Jones et al., 2004; Langlois & Roggman, 1990; Rhodes et al., 1998). The evolved cognitive and perceptual mechanisms seem to let an individual lacking reproductive fitness be perceived as unattractive (MacDorman et al., 2009). This in turn may produce a negative emotional response in order to avoid mating with this individual. Hanson (2005) demonstrated that highly attractive morphed robotic faces are rated low in eeriness. Hence, the experienced eeriness might also be explained as an evolved aversion to unattractive features, serving to increase reproductive success and ultimately, the preservation of one's own genes.

In conclusion, there is an abundance of research on the slow-processing theories which either have not been tested or yielded inconclusive, or even contradicting results. More recently, Haeske and Schmettow (2016) demonstrated a major involvement of the fast, rather than the slow, processing system by showing that eeriness ratings were reliably made even after a presentation time of only 100ms. Furthermore, Koopman and Schmettow (2019) showed that the uncanny valley effect is a universal experience and thus, exists independently of individual differences. These findings point towards a deeper underlying mechanism of fast-processing systems which has evolved as a mechanism benefitting homo sapiens' chance for self-preservation. The notion that the uncanny valley effect might be the product of evolutionary processes is further supported by its observable tendencies in monkeys. If the uncanny valley effect is not an exclusively human experience, it must have developed over the course of evolution, serving a purpose that human ancestors have profited from.

From Robotics to Primates

Taken together, based on the findings that the uncanny valley effect is universal, occurs within the first year of life, and is observable in monkeys, we argue that it is the result of an evolved fast-processing system which operates in anyone who has developed a face prototype. So far, evolution-theoretical approaches have been proposed but not yet tested (Moosa & Ud-Dean, 2010). Recently, Rádlová et al. (2018) have analysed different primate species according to their attractiveness as rated by humans but have not found any tendencies towards the uncanny valley as one would expect from the evolutionary aesthetics theory. Clearly, there is an urgent need to test the replicability of the phenomenon using biological stimuli in order to gather empirical data regarding its possible evolutionary origin and the involvement of fast processing systems.

Human-Likeness as Ancestral Closeness

The definition of the concept of human-likeness is still unclear (Zhang et al., 2020). In most experiments, human-likeness was assessed on the basis of participants' ratings (e.g. Mathur & Reichling, 2016). However, human-likeness cannot only be assessed on the basis of physical appearance but also as measured by phylogenetic closeness. Thus, we could assess an entity's level of human-likeness as a function of their ancestral closeness to the species homo sapiens. In this manner, we can observe whether an individual's emotional response may also be dependent on something that does not meet the eye but rather, is encoded in its genes. Just as the risk for disease contraction rises with closer genetic similarity (MacDorman et al., 2009), the uncanny feelings might increase as well, as a stimulus approaches ancestral proximity to homo sapiens. Therefore, we will investigate the stimuli's human-likeness and additionally, ancestral closeness.

Present Study

In the current study, we argue for a fast-processing system approach based on theories of pathogen avoidance and evolutionary aesthetics, and combine it with a developmental perspective on face processing. These theoretical considerations point towards an evolutionary origin of the uncanny valley effect. Comparable to the ontogenetic process of perceptual narrowing and developed expectations from social experience, the uncanny valley effect might be rooted in phylogenetic developments in which humans' perception has evolved to produce negative responses to highly humanoid entities. The phenomenon must not have developed to protect us from artificial agents but rather, in order to guide an individual's interaction with biological entities which needed to be fast and stimulus-driven. Therefore, the uncanny valley effect should be replicable using only biological faces, namely those of primates. To our knowledge, this has not been tested so far.

If the uncanny valley can be replicated using primate faces only, this would mean that mechanisms evolved to boost humans' chances for self-preservation are affecting modern interactions between humans and machines. In addition, this finding would support the fast-processing system theories such as evolutionary aesthetics and threat avoidance. An evolutionary explanation for the uncanny valley may aid in understanding what made us human and how this affects our response to humanoid entities in today's world. Ultimately, these insights might help in designing likeable human-like CG characters, as well as robots and androids.

We aim to examine two research questions. First, we investigate whether the uncanny valley effect can be replicated using primate faces. Therefore, we employ an online survey in which participants shortly view stimuli and rate them on visual analogue scales (VAS) for likeability and eeriness. Here, we analyse whether the response changes with varying levels of human-likeness based on expert ratings. Second, we investigate whether human-likeness as a function of ancestral closeness, meaning the phylogenetic proximity of stimulus and homo sapiens, can serve as a predictor for the negative emotional response typical for the uncanny valley. We divide the primate stimuli into 11 categories, following the last common ancestor principle.

Method

Procedure

The participants received a link to the online survey on qualtrics. On the first page, participants were welcomed and provided with a brief explanation of the study's procedure. They were told that the purpose of the study was to measure emotional responses towards different faces because knowing the proper purpose of studying the uncanny valley effect could have biased their responses. Next, the participants were asked to read the consent form and actively give consent by ticking a box (see Appendix A). After that, the participants were shown an overview of 16 stimuli to get an idea about the range of faces they would encounter in the following. Before the start of the experiment, the participants were given instructions for rating the faces on 2 scales. In order to ensure a proper understanding of the scale terms, participants were asked to select the language they were most proficient in out of the 3 available languages English, Dutch and German.

Upon stating that they had understood the instructions, participants were directed to the face ratings, consisting of 100 faces, shown in 4 blocks of 25 faces each. The participants viewed each stimulus for 2 seconds and then had to rate it on 2 scales, measuring its likeability and eeriness, respectively. After each block, the participants could take a short break before continuing with the next block. Upon completing the face ratings, the participants were asked to fill in 3 short questionnaires in English. These questionnaires were the Need For Closure Scale, the Very Short Authoritarianism Scale and the Short Big Five Inventory which were included for obtaining data for a substudy not elaborated on in this paper. After completing the questionnaires, the participants received a short debriefing about the purpose of studying the uncanny valley effect using biological faces.

Material

For this study, we created an online survey using the web-based survey tool Qualtrics (https://www.qualtrics.com/). The survey entailed a welcome page, an informed consent page, a page with an overview of the possible stimuli, an instruction page, the face rating part divided into 4 blocks, a questionnaire section and ultimately, the debriefing part.

Stimuli set

We used a total of 100 stimuli, consisting of 89 biological (i.e. primate) faces and 11 mechanical (i.e. robot and android) faces. The majority of the primate stimuli were obtained from John Gurche's catalogue of hominid busts with permission of the owner (https://gurche.com/), as well as from the open access databases Global Biodiversity Information Facility (https://www.gbif.org/) and PrimFace (https://visiome.neuroinf.jp/primface/). The remaining primate stimuli were acquired from free stock image sites and through targeted google image searches for facial expressions and different human ethnicities. We aimed to select a broad variety of primate species, ranging from relatively low to high human-likeness.

All primate stimuli had to fit the inclusion criteria adopted and changed from Mathur and Reichling (2016; see Appendix B). The primate stimuli were independently rated on human-likeness and emotional valence by 4 experts who conducted the experiment together. The individual human-likeness scores were tested for inter-rater reliability using a two-way fixed effects model, absolute agreement and average measures ($\alpha = .98$). Stimuli with a specifically low level of inter-rater agreement on human-likeness were excluded from the study, resulting in the aforementioned 100 stimuli.

The 11 mechanical face stimuli were selected from the study of Koopman and Schmettow (2019) which were originally gathered and rated on human-likeness as part of previous studies (Mathur & Reichling, 2016; Slijkhuis & Schmettow, 2017). The set of robot faces were selected to include stimuli covering the whole range of human-likeness (see Appendix E). In the future, this set of 11 stimuli can serve as anchor points to triangulate between robotic and biological faces. After the selection, each of the 100 faces was centralized, adjusted in size, singled out and set against a white background using Adobe Photoshop.

Ancestral Closeness

Furthermore, we categorized all stimuli according to their ancestral closeness. The phylogenetically further away a stimulus is from homo sapiens, the higher its assigned number for ancestral closeness. The stimuli were identified regarding their species and then grouped according to their last common ancestor (Primate, 2021). In other words, stimuli belonging to one group have in share their most recent ancestor which is a species that they all descended from (Most recent common ancestor, 2021). For instance, stimulus number 30 and 31 are different primates but they both belong to group 8 because they share their last ancestor which are the simians. As a result, we have obtained 11 groups, ranging from homo sapiens (0) over homininae (5) to robots (10) (see Appendix D for full categorization).

Measures

We asked the participants to rate each face on two visual analogue scales (VAS). For all scales, the participants were presented with the same statement ("To me, this face seems…") which they had to end by moving the slider on the VAS to the position which most accurately described their feeling. First, the one-item likeability scale was adopted from Mathur and Reichling (2016) and ranges from -100 (less friendly, more unpleasant, creepy) to 100 (more friendly and pleasant, less creepy). The likeability scale was displayed for every stimulus and every participant.

Second, we used the "spine-tingling" subscale of the eeriness index as revised by Ho and MacDorman (2017), consisting of 5 item pairs. The scale ranges from 0 to 100 with the item pairs at each end being "uninspiring - spine-tingling", "boring - shocking", "predictable - thrilling", "bland - uncanny" or “unemotional - hair-raising” (see Table C2). We employ this VAS rather than a categorical Likert scale because it allows participants to make continuous ratings which are more appropriate for determining how eerie an entity is. In more recent evaluations by Schmettow (2021, Chapter 6.8.4) the eeriness scale presents a good test-retest reliability. Koopman and Schmettow (2019) have used a previous version of the scale which was also translated to Dutch and German. We used these translations in order to eliminate any errors due to the language barrier and guarantee a thorough understanding of the terms (see Appendix C). For every participant, each of the 100 stimuli was randomly paired with 1 of the 5 eeriness item pairs.

Participants

In total, 82 participants took part in this study of which 4 had to be excluded due to too many missing values in their responses. The final number of participants included for analysis was 78. With regard to the research question and the findings for universality by Koopman and Schmettow (2019), we have decided not to obtain demographic data. Participants were recruited by means of convenience sampling through the researchers’ social environment and the test subject recruitment system SONA of the Behavioural, Management and Social Science (BMS) faculty of the University of Twente. Students who participated through SONA were granted credit points needed for the completion of their studies. The participants were required to be at least 18 years old, free of any major visual impairments and have a proficient level of English. All subjects took part voluntarily and have given informed consent prior to starting the study. This study was approved by the Ethics Committee of the BMS faculty of the University of Twente.

Design

We used a within-subjects design where every participant rated all stimuli on differing items of the scales. The dependent measures were the eeriness score and likeability score of the stimuli as rated by the participants. The eeriness score was obtained by averaging the participants’ responses to the different scales over the stimuli. The likeability ratings were not used for further analysis as the eeriness score have sufficed for the analysis of the uncanny response.

The independent variables were human-likeness, emotional valence and ancestral closeness. Emotional valence describes whether the emotion displayed by the stimulus is rather negative (-100) or positive (100). For human-likeness and emotional valence, we each took the mean of the 4 expert ratings to calculate the final score. Ancestral closeness is a variable with 11 values, with stimuli being coded on the basis of the aforementioned last common ancestor principle (see Appendix D).

Data Analysis

For the data analysis in R, we followed the suggestions by Schmettow (2021; see Appendix E for the data analysis protocol (DAP) created by Schmettow, 2021). First, the independent variable human-likeness was calculated from the average of the 4 expert ratings. Second, the participants’ eeriness responses were averaged over the stimuli. The eeriness variable was rescaled by a factor of 0.999 which was necessary for analysing the continuous responses to the eeriness VAS using a beta regression. For this type of regression, the values needed to be within the range of 0 and 1, excluding 0 and 1 specifically. Next, we calculated the correlation between the predictor human-likeness and the variable ancestral closeness by means of the Pearson correlation coefficient. For further analysis we only included the non-human primate stimuli and the eeriness scores. Some participants had a few missing values, yet were still useful and thus, included in the analysis.

Population-Level Analysis

First, we employed and visualised a simple regression analysis with human-likeness as independent variable and the averaged eeriness as predictor. This allowed for a first look at the data without a complex model. Next, we estimated 4 polynomial models from grand mean (0), to linear (1), quadratic (2) and cubic (3) using the Markov chains Monte Carlo (MCMC; see DAP in Appendix E; Schmettow, 2021). Here, we included emotional valence as a control variable. To determine which model fits best to explain the relationship between human-likeness and eeriness, we compared the predictive accuracy of the 4 polynomial models, using the leave-one out (LOO) approximation and information criterion (IC; Schmettow, 2021). The LOO method makes use of only one of the observations that is used to train the model. The remaining observations are used to evaluate its predictive accuracy which is provided in the form of the IC. The lower the value of the IC, the better is the model's predictive accuracy. We compared the LOO-IC of the 4 models and selected the one fitting best.

Next, we checked the probability of there being an uncanny valley curve on population level by means of the MCMC walks which are a Bayesian sampling method. This builds on 3 conditions which an observation must fulfill in order to be considered an uncanny valley curve. The graph must have a shoulder, i.e. the highest point before the valley, and a trough, i.e. the valley. Additionally, the shoulder must be left to the trough ($x_{trough} > x_{shoulder}$). Using the first and second derivative, we estimated the two stationary points and determined which one of them is the local minimum, the rough, and local maximum, the shoulder. We checked whether these conditions are fulfilled in all iterations of the MCMC for the selected model and calculated the ratio of how many iterations do and how many do not meet the uncanny valley conditions. This ratio subsequently determined the probability of obtaining an uncanny valley curve on the population level.

Multilevel Analysis

Second, we employed a multilevel model and integrated the prior model on population-level with the data on participant-level. This allowed us to observe the individual curves in relation to the population. We did this by grouping by participant and computing individual polynomials for every participant. Due to the nature of the VAS which is bound on 2 sides, a Gaussian distribution with mean variance was not suitable. Instead, we used a model in which the distribution of randomness is also bound on 2 sides. VAS are self-report measures so they do not have the same arithmetic properties as objective measures of eeriness would. This makes them prone to effects of introspection and anchoring, meaning that the participants' response styles may vary depending on how they interpret the endpoints and exploit the scale (Schmettow, 2021). For instance, one person might anchor, or mentally set, the lower point for eeriness higher than another person and vice versa. In order to account for these differences, we utilized a distributional beta regression which enabled us to adopt response variance on participant-level as an additional parameter (Schmettow, 2021). Then, one curve per participant was visualised. Again, we used the LOO-IC to calculate and compare the predictive accuracy of the model with and without the beta distribution.

Universality

Third, we utilized the selected model to check the universality of the uncanny valley. Again we checked the uncanny valley conditions and calculated the probability of obtaining an uncanny valley curve on participant-level. The position of individual trough and shoulder, as well as the probability for obtaining an uncanny valley, were visualised for every participant.

Results

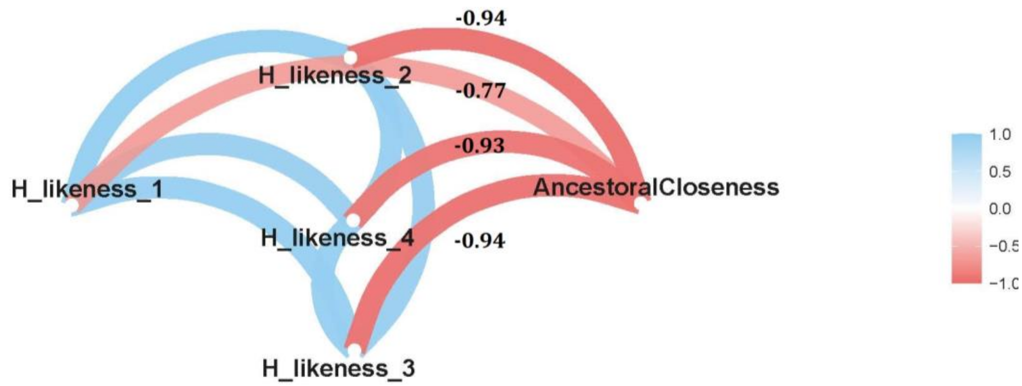
We investigated whether we can replicate the uncanny valley effect using primate faces and if so, whether ancestral closeness, next to the rated human-likeness, can serve as a predictor for the negative emotional response towards highly humanoid stimuli. In this section, we report the results obtained from the data, beginning with the role of ancestral closeness and continuing with the outcome of the explorative analysis. Most importantly, we look at the results of the models on population-, multi-, and participant-level. Lastly, we report the results for universality of the uncanny valley effect.

Ancestral Closeness and Human-Likeness

To begin with, we calculated the correlation between the 4 human-likeness ratings and ancestral closeness. The 2 variables are highly, yet negatively correlated with each other (see Figure 2) because the values on human-likeness are inverted to the categories of ancestral closeness which become "less human" as the value increases. All 4 human-likeness ratings have a good correlation ($\rho > .77$) and 3 of them have an almost perfect correlation ($\rho > .92$; see Table E1). We did not use ancestral closeness as a predictor for the eeriness response because with the high correlation of the 2 variables, it does not add any predictive value. However, the implications of this correlation are still of interest and will be discussed further.

Figure 2

Network plot of 4 human-likeness ratings and ancestral closeness



Population-Level Model

The simple regression model of human-likeness and eeriness provided a first look at our data where we can see a small trough around the human-likeness value of .5 (see Figure 3). Also, as each point represents one stimulus, we can observe that our stimuli set covers a great variety of human-likeness. We estimated and compared the 4 polynomial models using the LOO approximation and the IC in which case the first degree polynomial is the preferred one, as it has the lowest IC value (= - 268.7, see Table 1). Thus, when observing the data from the population as a whole, the linear model best predicts the responses of the participants in a continuous form. However, as the relationship is displayed as linear, we could not observe the typical uncanny valley curvature. Using the MCMC walks, the probability of obtaining an uncanny valley curve on population level was moderately good (= .63).

Figure 3

Plot visualising simple regression of mean eeriness response on human-likeness.

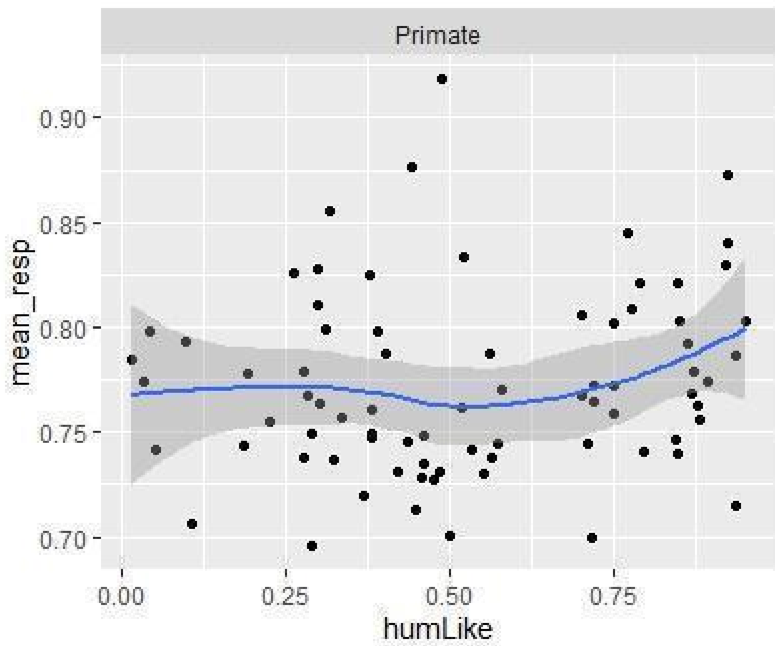


Table 1

Polynomials ranked by their predictive accuracy (LOO-IC)

Model	IC	Estimate	SE	Diff_IC
M_poly_1	looic	-268.70	12.25	0.00
M_poly_0	looic	-268.16	12.20	0.54
M_poly_2	looic	-266.50	13.08	2.20
M_poly_3	looic	-264.31	13.13	4.39

Multilevel Model

We employed a multilevel model which models the data on population- and participant level and visualizes all individual curves in one graph. Although on population-level the first degree polynomial model is the preferred one, we selected the third degree polynomial model for further analysis as it yielded a better fit on participant-level. The importance of the participant level analysis becomes apparent as we consider the aforementioned effects of anchoring and introspection. Due to the responses being averaged when looking at the data on population-level, the first degree polynomial seemed to fit better at a first glance.

However, when looking at the participants' individual polynomials plotted in one graph (see Figure 4), it becomes clear that on the population-level, the participants' differences in anchoring visually distorted the trend of the curvature. The varying individual intercepts shifted the individual curves vertically and made them appear almost parallel to each other (see Figure 4). Here, it is obvious why the analysis on population-level was not sufficient to observe the uncanny valley effect. Using the multilevel model instead, we visualized the individual polynomials next to each other to better discern the typical uncanny valley curvature. This curvature became even more distinct upon observing the individual curves displayed as one graph each (see Appendix Ex; see Figure 5 for an excerpt).

Figure 4

Spaghetti plot of multilevel model with individual uncanny valley curves

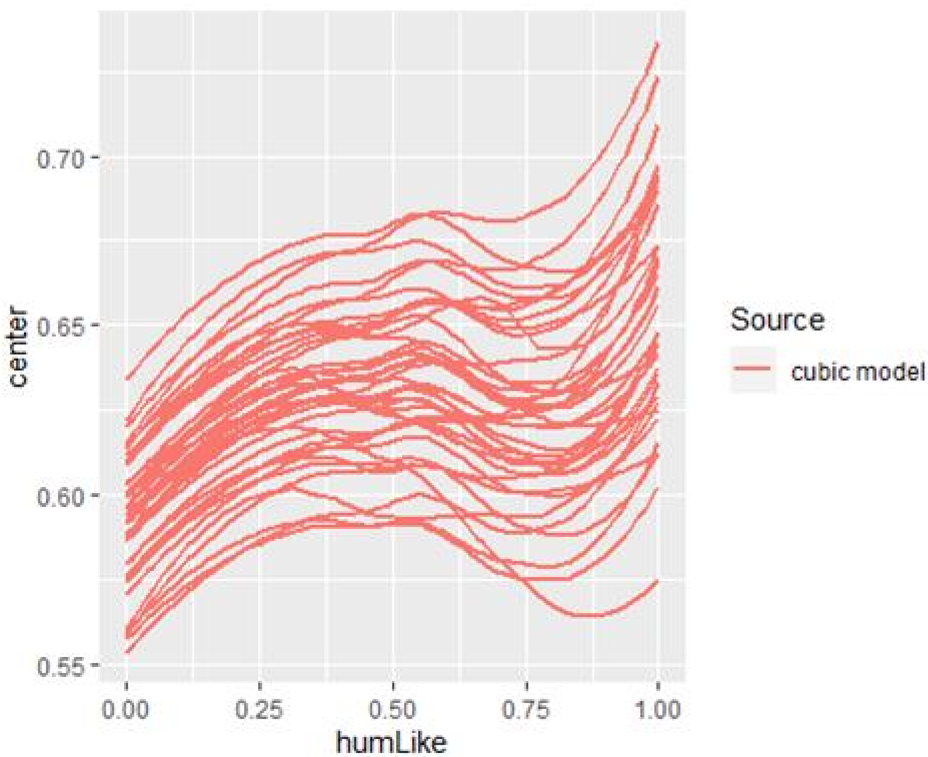
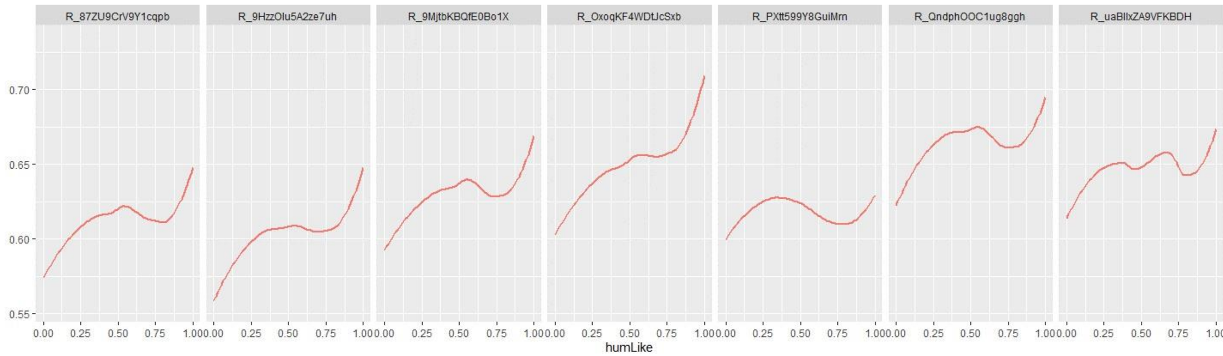


Figure 5

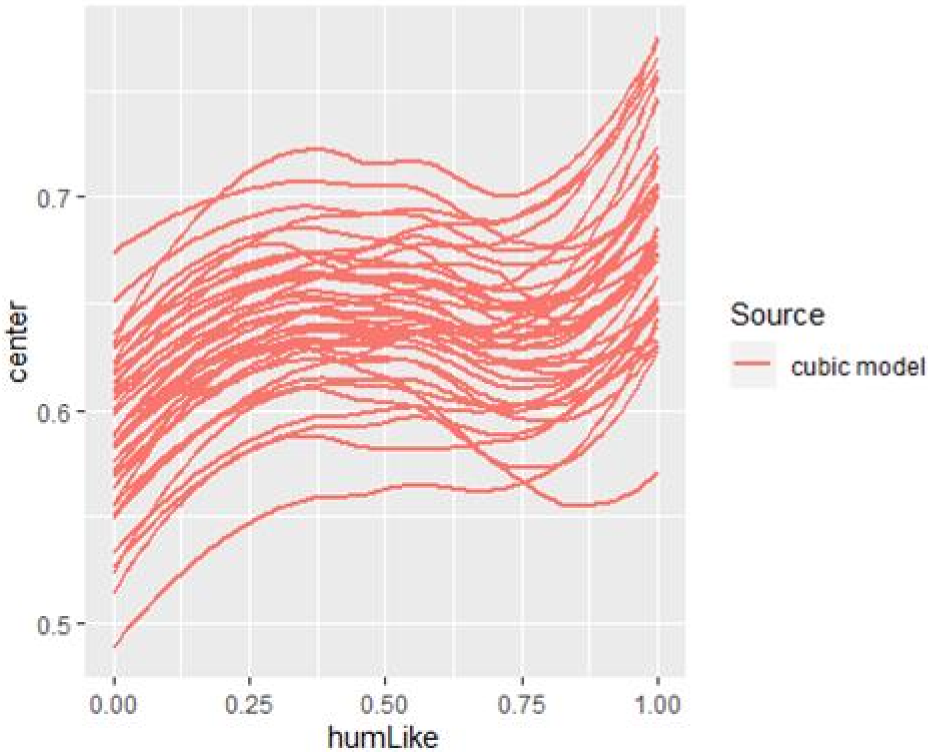
Excerpt of individual curves displayed separately from the population.



Next, to account for the differences in participants' responses due to differences in anchoring and introspection, we introduce a distributional beta regression which allows for varying response variance. The final model consists of a fixed-effects third degree polynomial with a participant-level random effect and a beta-shaped random distribution (see Figure 6). Again, we visualize the individual curves

Figure 6

Spaghetti plot of multilevel model with distributional beta regression



Universality

We employed the multilevel model with the beta distribution to check whether the uncanny valley effect is a universal experience. In this case, almost every participant's responses fell into the uncanny valley with a probability of 70% or higher for obtaining a curve with a shoulder, a trough and x_{trough} being larger than $x_{shoulder}$. However, there was one outlier that had a low probability of 31.57% (see Figure 7). This participant also stands out in the violin graph (see Figure 8) because their shoulder and trough are very close to each other. Therefore, we could not observe the uncanny valley effect as a universal experience. Despite the aforementioned shift of the intercept between subjects, we could still observe a sense of continuity in the participants' curves. We visualized the position of the shoulder and trough for every participant by means of a violin graph (see Figure 8). The position of the shoulder was relatively stable across the participants at a human-likeness score of around .25 to .3. The trough, on the other hand, had a more varying position of around .6 to .8 of the human-likeness.

Figure 7

Individual probabilities of obtaining an uncanny valley curve per participant

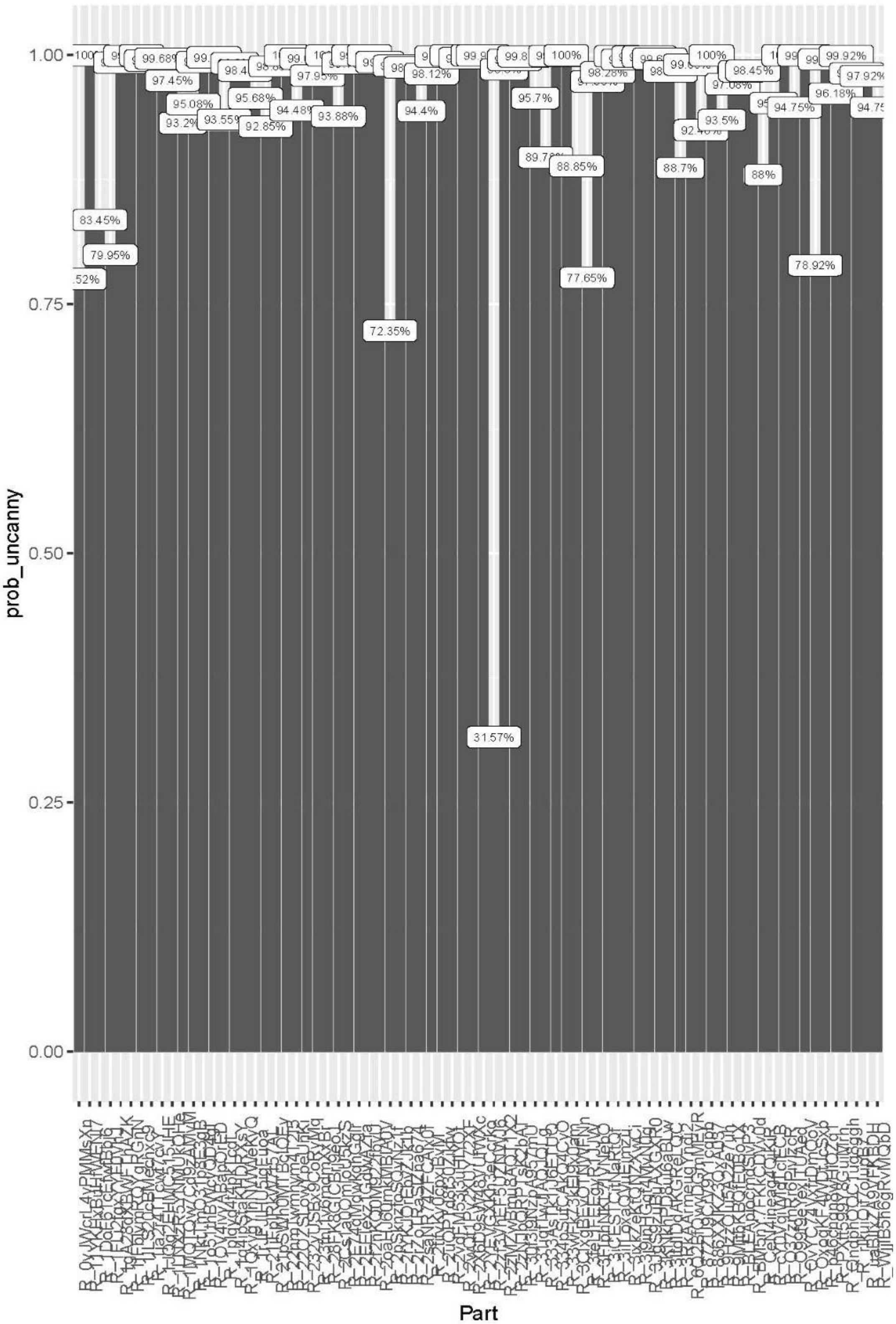
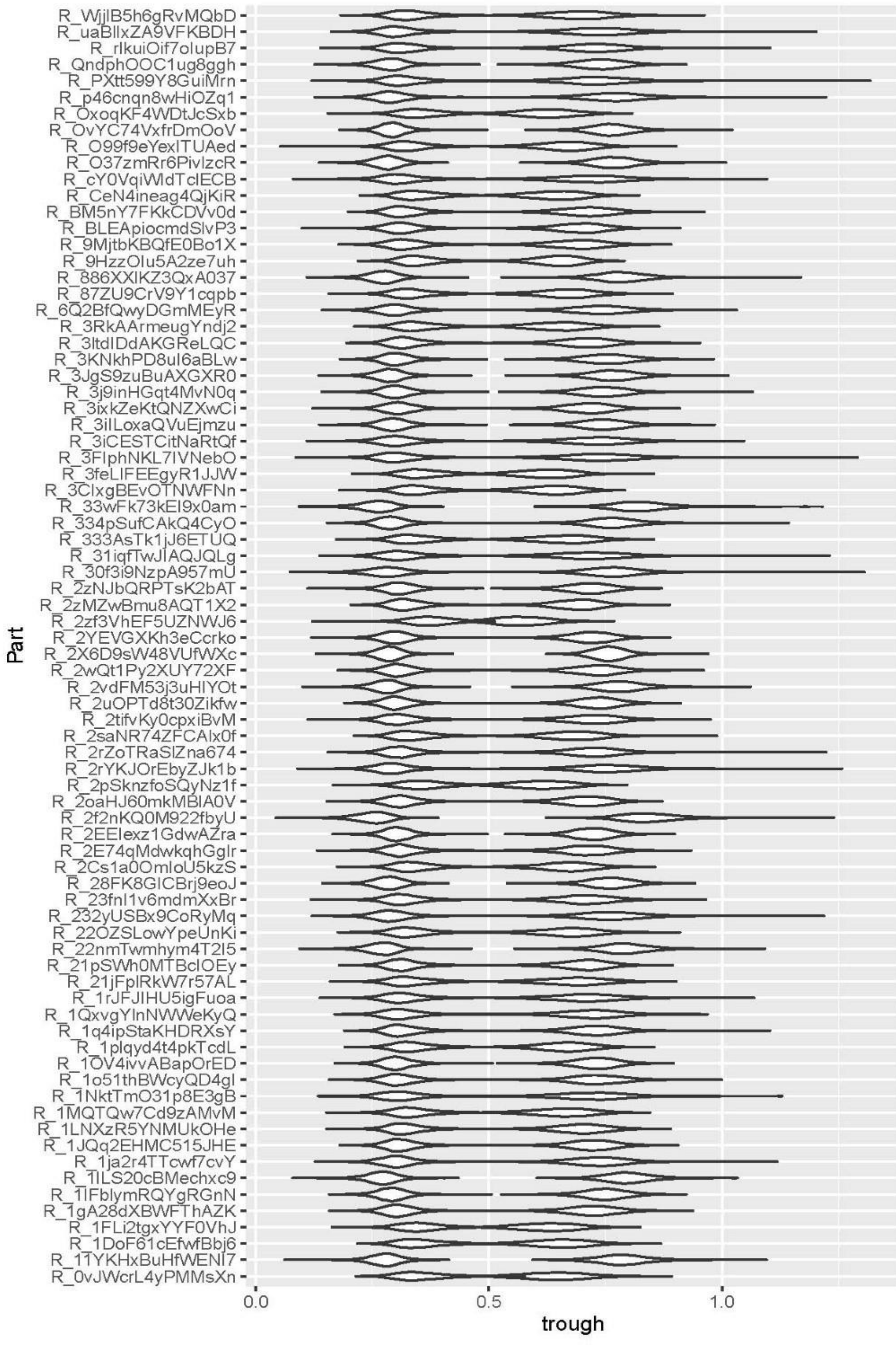


Figure 8

Violin graph displaying position of shoulder and trough for every participant's curve



Visibly white sclera

Unexpectedly, we have found a shared characteristic for stimuli falling into the uncanny valley. We checked the stimuli corresponding to the human-likeness level in the trough and noticed that all primates and even the robots here have a visibly white eyeball, also called sclera (see Figure 8). Only 2 out of the 13 primate faces in the uncanny valley did not exhibit this feature, while all robot faces did.

Figure 8

Examples of Stimuli With Visibly White Sclera Falling into the Trough

Discussion

In this study, we aimed to replicate the uncanny valley effect by employing an online study using primate faces, instead of robotic or CG faces. This was prompted by the notion that the uncanny valley effect might be the result of evolutionary processes which build on research findings that monkeys experience the same effect. Furthermore, results of recent studies suggested a major involvement of fast-, as opposed to slow-processing systems. In the present study, we demonstrated that humans also experience the uncanny valley effect when viewing highly human-like biological stimuli.

Replicating the Uncanny Valley Effect

We were able to replicate the uncanny valley effect using primate faces which, to our knowledge, is the first time that this has been achieved. Thus, we can positively affirm our first research question. The uncanny response is not bound to artificial entities such as robots and CG avatars but occurs with primates as well. Moreover, we found a close correlation between the stimuli's human-likeness and phylogenetic proximity to homo sapiens. Hence, the concept of ancestral closeness can serve as an objective measure for human-likeness of biological stimuli. On the basis of these findings we suggest that the uncanny valley effect is not a recently emerged phenomenon but rather, the result of early evolutionary adaptations in humans' phylogenetic development. According to evolution theory, all psychological structures innate to humans have once evolved under the selection pressure and are still active in today's time (Carroll, 1995). This implies that, although the uncanny valley effect continues to influence humans today, its underlying mechanisms have once evolved because they aided human ancestors in increasing their chances for self-preservation. With the knowledge derived from our study, we can begin to detach the uncanny valley phenomenon from the field of robotics and start approaching it from an evolutionary-psychological perspective.

Advances in Modelling the Uncanny Valley

Just as Mathur and Reichling (2016), we found that the third degree polynomial is the best fit for visualising the uncanny valley curve. However, this was only the case once we had modelled the relationship of human-likeness and eeriness response on the participant level. With the current self-report measures used in the research around the uncanny valley effect, it is crucial to shift the focus of the analysis from the population level to the participant level as well (Schmettow, 2021). As mentioned before, the nature of the used eeriness measures makes results prone to falling victim to effects of introspection and anchoring. Thereby, the individuals' differing response styles make the intercepts shift so that they are almost parallel to each other. Thus, when we look at the results of the entire sample visualized in one curve, the uncanny valley curve that is visible on the participant level, is distorted. In this study, we have circumvented this issue and paved the way for analyses in future research around the uncanny valley.

Universality

In contrast to a recent study by Koopman and Schmettow (2019), we did not observe universality of the uncanny valley effect in our study. Nevertheless, we got a moderately high probability of obtaining the uncanny valley curve for almost every participant. This finding may be explained by considering the face prototype as a strictly necessary prerequisite for experiencing the effect. This means that, although the phenomenon must be the result of evolutionary processes which all humans share, its exhibition depends on developmental processes as well. This notion is in line with the aforementioned findings of Feng et al. (2018) which demonstrate that not normally developing individuals, such as children with Autism Spectrum Disorder (ASD), do not exhibit the effect. Therefore, the uncanny valley effect might only be a universal experience to those individuals who have developed a human face prototype. We assume that one of the participants in the current study did not develop a face prototype and thus, did not experience the uncanny valley effect.

Additionally, the position of the shoulder was relatively stable for all participants, meaning that overall, the uncanny valley effect is elicited at the same level of human-likeness for all participants. The differences in the intercepts of the individual curves come about because every individual exploits the rating scales differently and thus, there are varying response styles. We accounted for this by adopting a model that takes into account these participant random effects. The findings of overall high probabilities for obtaining an uncanny valley curve and its stable shoulder position challenge the slow-processing system approach arguing for the role of individual differences in bringing about the phenomenon (MacDorman & Entezari, 2015). Instead, our findings corroborate the fast-processing system and evolution-psychological approach.

Explaining the Effect's Absence in Previous Research

Interestingly, previous study on physical attractiveness did not demonstrate tendencies towards the uncanny valley (Rádlová et al., 2018). In part, our stimuli set overlaps with the groups identified by Rádlová et al. (2018) as both cover the prosimians and catarrhini. However, in the present study, we do not have stimuli comparable to their low end of human-likeness but have therefore extended the high end human-likeness to include species closer to homo sapiens. Their findings regarding the uncanny valley were ambiguous as some stimuli did fall into the valley, while others did not. Besides their consideration that ratings of attractiveness may be partly distinct from the concept of human-likeness, we suggest another explanation for their results. Within their group of primates phylogenetically closest to homo sapiens (i.e. catarrhini), they obtained the highest attractiveness ratings. In the current study, the catarrhini were the primates on the lower end of ancestral closeness. Thus, the most human-like stimuli of Rádlová et al.'s (2018) study and the least human-like stimuli in our study overlap. Therefore, we argue that their study merely covered the stimuli of low to moderate human-likeness, thereby, staying just before the shoulder of the curve.

An Evolutionary Mechanisms Against Interbreeding

As we found human-likeness and ancestral closeness to be nearly perfectly correlated, we can assume that phylogenetic proximity of biological stimuli is just as important as the human-like appearance of artificial stimuli. The fact that ancestral closeness of stimuli to humans is almost perfectly correlated with subjective human-likeness ratings suggests that the phenomenon stems from times in which homo sapiens were exposed to other, closely human-like species. Possibly, the uncanny valley effect has evolved as a mechanism shielding human ancestors from interaction and interbreeding with other species. If an encountered individual came close to, yet did not match the prototype, human ancestors could have avoided it instead. Ultimately, this would be in line with the theories of threat avoidance and evolutionary aesthetics which all served the purpose of securing self-preservation through increasing reproductive success. If so, this mechanism for mating success continues to affect our perception and evaluation of human-like entities today. In the following, we will consider which advantages the development of the uncanny valley phenomenon might have brought about and what they can tell us about what made us human.

Evolutionary Advantages of Visibly White Sclera

The finding that nearly all stimuli falling into the valley have a visibly white sclera implies that the eyes may play a decisive role in the eeriness response. This is in line with the aforementioned finding of

Looser and Wheatley (2010) stating the eyes' importance for assigning animacy to an entity. However, in order for this feature to elicit the eeriness response, one would assume that it already comes about in the portion of the curve after the shoulder, where the response starts to become less positive. This is not the case and so although having a visibly white sclera might not cause the uncanny valley effect, it might well be implicated in strengthening the negative response which we find in the trough.

According to Kobayashi and Kohshima (2001), the visibility white sclera has several evolutionary implications. It can be found in close human ancestors but is largest and most horizontally elongated in humans, as compared to other primate species. The amount of visibly white sclera increases as we move along the phylogenetic tree towards homo sapiens, and with body size, especially with an upright walking height. The elongated eye with a higher sclera proportion enables an extended horizontal visual field which became increasingly important as human ancestors moved from arboreal to terrestrial habitat. That is because terrestrial species need the horizontal scanning of their environment more than arboreal ones. Furthermore, the white sclera is often thought of as a sign of good health and is associated with attractiveness and age (Tomasello et al., 2007, Provine et al., 2013). More importantly, it serves as a means for communication. According to the cooperative eye hypothesis (Kobayashi & Hashiya, 2011; Kobayashi & Kohshima, 1997; Tomasello et al., 2007), it has evolved in humans for the purpose of non-verbal communication via shared attention and gaze direction (Segal et al., 2016). The white portion around the darker iris enables individuals to discern the gaze direction of another individual which can help to identify their object of attention (Kobayashi & Kohshima, 2008). Thus, the white sclera seems to have developed in terrestrial species because it posed an advantage for them and enhanced their communication which ultimately aided individuals and their group to survive.

Eeriness and Visibly White Sclera

The evolutionary advantages of the white sclera would let us assume that it is a trait perceived as favourable. However, the white sclera is exhibited by stimuli in the valley. We might explain this finding by considering how faces are being processed. Due to the high human-likeness of these stimuli, the participants were very sensitive to the stimuli in Figure 8, which enabled them to discriminate well whether the stimuli are human or not. Since they are non-human, the participants could have further used featural processing for evaluation. However, upon processing the eyes, which are a feature of high diagnostic value, participants may have identified those faces as human due to the visibly white sclera. The visibly white sclera is, to this extent, unique to humans and hence, could be part of the human face prototype. These conflicting ideas could have led to category confusion which ultimately, resulted in the extreme eeriness response. Although the category confusion theory was rejected as a cause for the uncanny valley (Mathur et al., 2020), it might still be involved in making the negative response even stronger. We do not consider the visibly white sclera as a necessary trait for evoking the uncanny response but rather as a feature which amplifies the emotional appraisal.

Interestingly, recent research has demonstrated that this feature is not limited to human communication but also plays a role within human-robot interaction. Perugia et al. (2021) found that a shared gaze for an object of joint attention, rather than a gaze at the robotic partner, is an important predictor for engaging in a task. This further supports the idea that the white sclera plays a role in the uncanny valley effect because it enables following another one's gaze which seems not only to be important in interaction between humans but also with robots.

Support for Fast-Processing Systems

With the finding that the uncanny valley effect emerges for primates, we have found support for the fast-processing system theories which claim that the phenomenon is an evolved, automatic and stimulus-driven process. The categorical uncertainty theory belongs to the slow-processing system approaches and has been impugned by Mathur et al. (2020) who found that the category boundary does not coincide with the uncanny valley. They suggested that the differing degrees of feature realism combined in one entity might be underlying the eerie response instead. However, since we were able to replicate the uncanny valley effect with unmanipulated primate faces of consistent realism, we can oppose the realism inconsistency theory. Although inconsistent realism may strengthen the uncanny response, it is not what is eliciting the effect in the first place. Instead, with the finding of the visibly white sclera in primates falling into the valley, we reconsider the category uncertainty theory, not as the only explanation for the effect's origin but rather as an approach that can contribute evolutionary explanations.

Limitations

In the current study, we have utilized the five scales belonging to the spine-tingling subfactor of the eeriness index which, however, originally consists of seven scales in total (Ho & MacDorman, 2017). The results of our analysis could have been even stronger if this study had included the additional three scales of the eerie subfactor. If the study is replicated in the future, including the eerie subscale next to the spine-tingling one, researchers should observe whether there are differences in the responses to the two subscales. If so, these differences might reveal new insights into what exactly the uncanny response entails.

Moreover, some participants have indicated that they found it difficult to rate the stimuli based on the applied scales. One participant commented that they were "often unsure about the answer possibilities as both did not exactly fit to what [they were] feeling". This kind of remark has occurred repeatedly in previous studies as well (Koopman & Schmettow, 2019; Haeske & Schmettow, 2016) where participants felt that the item pairs of the eeriness scale do not constitute polar opposites. However, this notion describes the unipolarity of the eeriness scale which does not make it an unsuitable measurement tool but rather one that participants might not be used to. Individuals who have experience in participating in research might be used to filling in scales with item pairs of opposite nature. In this case, the concept of eeriness can be assessed with such a unipolar scale because we specifically want to measure the extent to which something appears eerie.

To date, there are no objective indices for measuring the eeriness response which makes the generalizability of experimental results rather difficult (Zhang et al., 2020). Despite this limitations, we were still able to show pronounced uncanny valley curves, hence, speaking for the strength and quality of the eeriness index. This also becomes evident as we consider other studies which have used versions of this measurement tool and demonstrated the uncanny valley effect as well (Koopman & Schmettow, 2019; Slijkhuis & Schmettow, 2017). In conclusion, the limitations in this study should be considered for future research but do not constitute a restraint to our findings.

Future Research

With the finding that the uncanny valley effect can be replicated using primate faces, we have opened many doors for future research. We have compiled a stimuli set that can be reused for replicating the uncanny valley effect in different populations to further research its universality. Furthermore, future research should investigate a larger variety of primate species, ranging from those included in the study of Rádlová et al. (2018) to the ones included in the current study. The results of such a study could provide empirical support for our suggestion that Rádlová et al. (2018) have missed the uncanny valley due to their selection of primate species.

Next, future studies should investigate the role of a visibly white sclera for the uncanny response. For instance, they should conduct a study in which the colour of the sclera for various primate species is manipulated. Just as in the current study, the researchers could use a set of primate faces, or use the set compiled by us, including some stimuli with a visibly white sclera. The participants should be divided into two groups, namely a control and an experimental group, each viewing a different set of stimuli. The participants in the control group should view and rate the original primate faces with their natural sclera colour. In the experimental group, the primate faces with originally visibly white sclera should be manipulated so that the sclera is coloured, for instance brown or black to blend into the primate's overall appearance. The remaining stimuli without a white sclera serve as control stimuli, providing anchor points, to compare where the manipulated stimuli stand in comparison to natural stimuli. The data should be analysed as in the current study, using a fifth degree polynomial model, and the two groups compared regarding their individual and overall curve, as well as the probability of obtaining an uncanny curve. With the findings of our study in mind, we can expect to find a stronger eeriness response in the control group, as the white sclera in nearly human-like entities seems to trigger a more negative emotional appraisal.

Conclusion

The findings of the current study allow us to detach the phenomenon of the uncanny valley from the field of robotics and CG avatars and pave the way for a new perspective on how to approach it from an evolutionary perspective. Different developmental processes such as perceptual narrowing and exposure to certain faces define the type of face prototype an individual is sensitive to. The experience with conspecific's faces is crucial for a face prototype and for the uncanny valley effect to emerge. However, what brought about the phenomenon in the first place are evolutionary processes. In line with that, we have uncovered that this seemingly modern phenomenon stems from ancient times in which its underlying mechanisms helped human ancestors to survive and reproduce successfully. Although the exact underlying factors are not yet known, the evolutionary approach is promising and might even set the tone for other "modern" phenomena to be studied in the context of their possible evolutionary functions. Despite the remaining, we can certainly conclude that the uncanny valley effect has evolutionary roots, yet continues to affect modern humans in their interaction with technology such as social robots and CG agents.

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Appendices

Appendix A

Consent Form

Information for participation in the research study on humans' emotional response towards different faces

You are being invited to participate in a research study conducted as part of a bachelor thesis within the Faculty of Behavioural, Management and Social Sciences at the University of Twente. The aim of this research is to assess humans' emotional response towards different faces. Completing the study will take approximately 30 minutes and involves viewing images and answering survey questions.

Risks

To our understanding, there are no risks associated with this research study, however, some images might be sensitive or provoke personal discomfort. Given your participation in this study is entirely voluntary, you are free to withdraw at any time without providing any reasons or experiencing any disadvantages.

Handling of data and confidentiality

To the best of our ability, your answers in this study will remain confidential. We will minimize any risks by assuring that your participation in this study is anonymous, as no information will be collected that would allow personal identification. All data will be stored securely and will not be shared with anyone outside the research team. Any comments you make may be quoted in an anonymised form in the research papers resulting from this study.

Contact information

If you have any questions or concerns about this survey or wish for your data to be deleted you can contact the researchers via email:
Lara Geue (l.geue@student.utwente.nl),
Milan Bischoff (m.bischoff@student.utwente.nl),
Marcel Pertenbreiter (m.pertenbreiter@student.utwente.nl),
Jana Westermann (j.m.l.westermann@student.utwente.nl).

If you have questions about your rights as a research participant or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher, please contact the secretary of the Ethics Committee of the Faculty of Behavioural, Management and Social Sciences of the University of Twente (ethicscomittee-bms@utwente.nl).

Consent

I confirm that I have read and understood the information provided above and consent voluntarily to be a participant in this study. I further confirm that I possess a sufficient level of proficiency in English and that I am at least 18 years old.

❏ I consent.

❏ I do not consent to take part in this study.

Appendix B

Stimuli Inclusion and Exclusion Criteria

Criteria adapted and changed from Marthur & Reichling (2016)
Inclusion criteria:

1. All facial features and the outline of the face are discernable.
2. The face is shown in frontal to 3/4 aspect (both eyes visible).
3. The individual belongs to a species that has lived or is still living (no fictitious faces)
4. The image depicts
    a) A living individual
    b) real remainders of the animal that have been taxidermied to closely resemble the way it looked when it was alive, or
    c) A realistic hominid bust (no artificially created CG or morphed face)
5. In case if b) and c), it is shown as it looked when it was alive (not missing any hair, facial features or skin)
6. The resolution of the photo is sufficient to yield a final cropped image of 450x450 pixel.

Exclusion criteria:

1. The individual represents a famous person (for the human image)
2. The image shows other faces or body parts that would appear in the final image.
3. Objects or text overlap the face.

Appendix C: Face Rating Scales

Table C1

Likability scale translations

English	Dutch	German
Less friendly, more unpleasant, creepy	Minder vriendelijk, onaangenaamer, griezelig	Weniger freundlich, unangenehmer, gruselig
More friendly and pleasant, less creepy	Vriendelijker, aangenaamer, minder griezelig	Freundlicher, angenehmer, weniger gruselig

Figure C1

Likability visual analogue scale (VAS) with a3 slider in English.

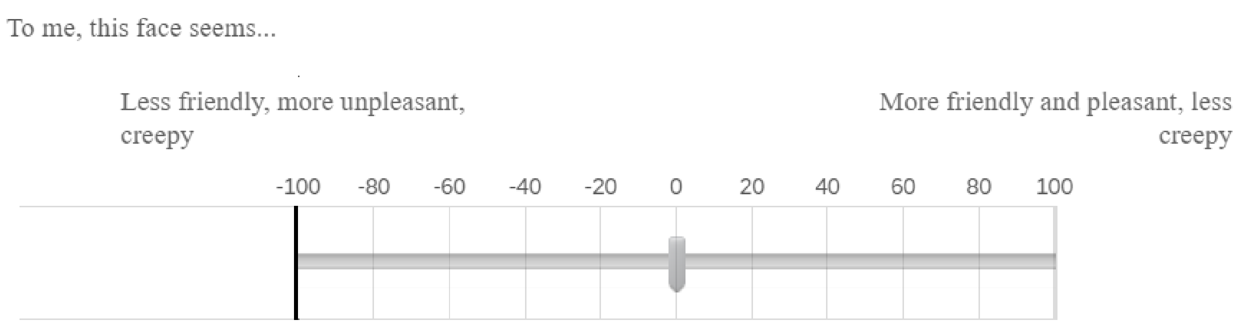


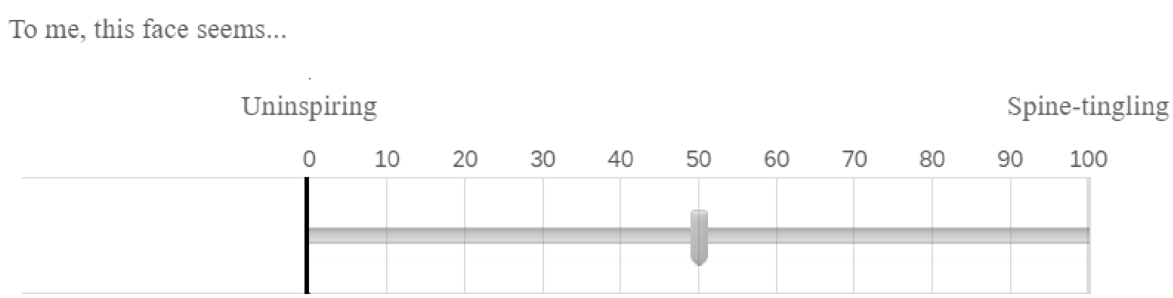
Table C2

Translations of the eeriness scales

English	Dutch	German
Uninspiring - Spine-tingling	Oninteressant - Opwindend	Uninteressant - Aufregend
Boring - Shocking	Saai - Schokkend	Langweilig - Schockierend
Predictable - Thrilling	Vorspelbaar - Spannend	Vorhersehbar - Spannend
Bland - Uncanny	Flauw - Verontrustend	Fade - Beunruhigend
Unemotional - Hair-raising	Emotieloos - Doodeng	Emotionslos -Haarsträubend

Figure C2

Eeriness VAS with a slider in English.



Appendix D

Stimuli Code Book

Table D1

Categorization of Ancestral Closeness According to Last Common Ancestor Principle

Code	Last common ancestor
0	Homo sapiens
1	Neanderthalensis
2	Homo Erectus/Naledi/Ergaster
3	Hominina (Homo Habilis, Australopithecus afarensis/africanus/sediba, Paranthropus Aethiopicus Boisei/Robustus)
4	Hominini (Panina Pan, Pan troglodytes/paniscus)
5	Homininae (Gorillini, Gorilla gorilla/beringei)
6	Hominidae (Ponginae, Pongo abelii/pygmaeus/ tapanuliensis)
7	Catarrhini (Old world monkeys (Cercopithecidae), Macaca)
8	Simians/Anthropoids/Higher order primates (New world monkeys (Platyrrhini), Callitrichidae, Tamarins/Marmosets)
9	Prosimians/Primates (Strepsirrhini, Lemurs)
10	Robots

Appendix E

Data Analysis Protocol

Inter-Rater Reliability Human-Likeness

```
icc(Stimuli_Ratings[, 3:6], model = "twoway", type = "agreement", unit = "average")
Average Score Intraclass Correlation

Model: twoway
Type : agreement

Subjects = 89
Raters = 4
ICC(A,4) = 0.977
F-Test, H0: r0 = 0 ; H1: r0 > 0 F(88,61.4) = 52.9 , p = 3.95e-38
95%-Confidence Interval for ICC Population Values: 0.962 < ICC < 0.985
```

The following code and output for the data analysis in R was created by Dr. Martin Schmettow.

Selection of Robot Faces for Comparison

Stimuli from Koopman and Schmettow (2019)

```
load("Uncanny.Rda")
attach(Uncanny)

## The following objects are masked _by_ .GlobalEnv:
##
##     M_poly_2, M_poly_3, P_univ_uncanny

## The following object is masked from package:uncanny:
##
##     trough

predict(M_poly_3) %>%
  left_join(RK_2) %>%
  mutate(Range = round(huMech * 100) %/% 10) %>%
  mutate(error = abs(avg_like - center)) %>%
  group_by(Range) %>%
  mutate(Best = (error == min(error))) %>%
  ungroup() %>%
  filter(Best) %>%
  select(Range, Stimulus, huMech, error) %>%
  arrange(Range)
```

```
## Joining, by = "Obs"
```

Table E1

Selection of Robot Stimuli

Range	Stimulus	huMech	error
0	3	0.0375	1.126914
1	15	0.1875	1.101790
2	22	0.2750	1.151271
3	28	0.3500	1.137703
4	32	0.4000	1.176306
5	42	0.5250	1.149822
6	50	0.6250	1.261915
7	59	0.7375	1.236049
8	68	0.8500	1.117708
9	74.2	0.9275	1.129486

```
detach(Uncanny)
```

Stimuli

```
Stimuli <-
  readxl::read_excel("Data/BA21/Stimuli.xlsx") %>%
  mutate(Stimulus = str_c("S", as.character(Stimulus))) %>%
  mutate(Set = factor(Set, 1:4, labels = c("Primate", "Human", "Tri23",
"Robot"))) %>%
  mutate(humLike = rowMeans(select(., starts_with("H_like")), na.rm = T)) %>%
  mutate(valence = rowMeans(select(., starts_with("E_valence")), na.rm = T))

Stimuli %>%
  sample_n(20)
```

Table 2

Excerpt of Primate Stimuli and Their Scores on Measured Variables

Stimulus	Set	H_likeness_1	H_likeness_2	H_likeness_3	H_likeness_4	E_1	E_2	E_3	E_4	E_valence_1	E_valence_2	E_valence_3	E_valence_4	AncestoralClosenesss	Ethnicity	humLike	valence
S78	Primate	55	65	65	55	1	4	4	1	65	80	40	70	4	0	60.00	63.75
S25	Primate	97	96	93	95	1	1	1	1	37	60	20	25	1	0	95.25	35.50
S72	Primate	82	75	65	70	0	0	0	0	-10	0	0	0	3	0	73.00	-2.50
S40	Primate	18	50	45	50	4	4	4	4	10	-20	-20	5	5	0	40.75	-6.25
S57	Primate	40	50	55	50	0	0	0	0	0	0	0	5	4	0	48.75	1.25
S84	Primate	97	90	94	90	5	5	5	4	80	-100	-95	-60	2	0	92.75	-43.75
S38	Robot	37	NA	NA	NA	4	4	4	4	30	0	-20	-15	10	0	37.00	-1.25
S54	Primate	2	10	15	5	5	0	0	0	-26	0	0	0	9	0	8.00	-6.50
S98	Human	100	100	100	100	4	4	2	4	85	0	-95	-70	0	1	100.00	-20.00

S42	Primate	94	90	90	85	1	1	1	4	33	50	30	5	2	0	89.75	29.50
S85	Primate	91	90	95	95	4	4	2	2	-25	-30	-90	-50	2	0	92.75	-48.75
S49	Tri23	100	100	98	97	1	1	1	1	60	70	50	10	0	0	98.75	47.50
S53	Primate	83	90	89	80	0	1	1	1	13	60	40	5	2	0	85.50	29.50
S76	Primate	80	80	82	80	0	5	0	0	0	-50	0	0	3	0	80.50	-12.50
S61	Primate	1	20	15	3	2	2	0	0	-20	-10	0	0	8	0	9.75	-7.50
S93	Human	100	100	100	100	5	6	6	6	-85	-60	-90	-70	0	1	100.00	-76.25
S12	Primate	24	45	25	25	4	4	2	4	70	-20	-80	-70	7	0	29.75	-25.00
S69	Primate	28	45	35	30	4	4	4	4	55	20	10	25	7	0	34.50	27.50
S43	Primate	45	50	60	40	0	3	0	0	-10	-50	0	0	4	0	48.75	-15.00

S37	Primate	70	85	80	70	6	6	1	1	-30	-20	90	20	3	0	76.25	15.00

Correlating Ancestral Closeness and Human-Likeness

```
Stimuli %>%
  select(starts_with("H_like"), AncestoralCloseness) %>%
  corrr::correlate()

##
## Correlation method: 'pearson'
## Missing treated using: 'pairwise.complete.obs'
```

Table E3

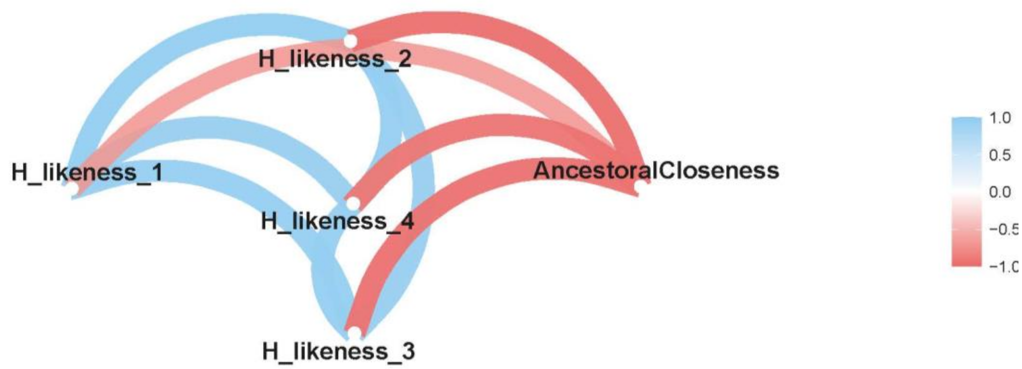
Pearson Correlation of Human-Likeness Ratings and Ancestral Closeness

H_likeness_1	NA	0.9554019	0.9436330	0.9328772	-0.7707424
H_likeness_2	0.9554019	NA	0.9303407	0.9426051	-0.9422645
H_likeness_3	0.9436330	0.9303407	NA	0.9438880	-0.9379207
H_likeness_4	0.9328772	0.9426051	0.9438880	NA	-0.9268578
AncestoralCloseness	-0.7707424	-0.9422645	-0.9379207	-0.9268578	NA

```
Stimuli %>%
  select(starts_with("H_like"), AncestoralCloseness) %>%
  corrr::correlate() %>%
  corrr::network_plot()

##
## Correlation method: 'pearson'
## Missing treated using: 'pairwise.complete.obs'
```

Figure E1

Network Plot of Human-Likeness Ratings and Ancestral Closeness



Reading and Preparing Data

```
D_raw <-
  readxl::read_excel("Data/BA21/Final Dataset Uncanny Valley 16-05-21.xlsx")
%>%
  filter(StartDate != "Start Date")

BA21 <- D_raw %>%
  select(Part = ResponseId, matches("^S\\d+")) %>%
  pivot_longer(-Part, names_to = "Trial", values_to = "response") %>%
  filter(!is.na(response)) %>%
  separate(Trial, into = c("Stimulus", "Item", "attempt")) %>%
  left_join(Stimuli %>% select(Stimulus, Set, valence, humLike), by =
"Stimulus") %>%
  mutate(Scale = if_else(str_detect(Item, "^2"),
                         "Eeriness",
                         "Display"),
         response  = mascutils::rescale_unit(as.numeric(response)),
         response  = mascutils::rescale_centered(response, scale = .999),
         humLike   = mascutils::rescale_unit(humLike),
         #Stimulus = str_extract(Trial, "^S\\d{2,3}_\\d"),
         #Item     = str_extract(Trial, ),
         #humLike  = as.numeric(str_extract(Stimulus, "\\d{1,3}")),
         humLike_2 = humLike^2,
         humLike_3 = humLike^3) %>%
  bayr::as_tbl_obs()
BA21

BA21_prim <-   BA21 %>%
  filter(Set == "Primate")

BA21 %>%
  group_by(Part) %>%
  summarize(N = n())
```

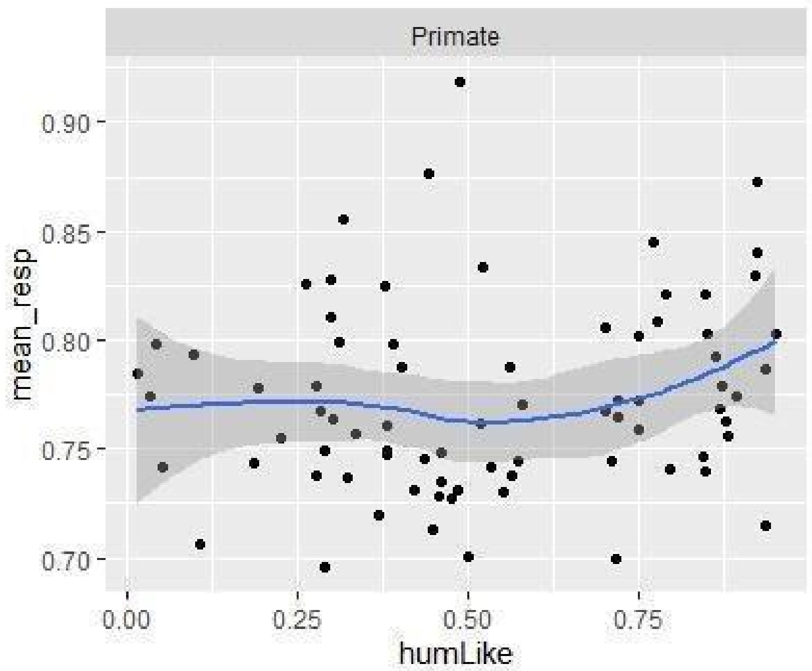
```
BA21 %>%
  group_by(Stimulus) %>%
  summarize(N = n())

BA21_agg <-
  BA21_prim %>%
  filter(Scale == "Eeriness") %>%
  group_by(Stimulus, Set, valence, humLike) %>%
  summarize(mean_resp = mean(response, na.rm = T)) %>%
  ungroup() %>%
  as_tbl_obs()


BA21_agg
```

For a first look at the data, we average the eeriness responses over the stimuli so that every stimulus is assigned an eeriness score.

```
BA21_agg %>%
  ggplot(aes(x = humLike,
             y = mean_resp,
             size = valence)) +
  geom_point() +
  geom_smooth() +
  facet_wrap(~Set)

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

Figure E2

Plot visualising simple regression of mean eeriness response on human-likeness.



Population-level model

We estimate four polynomials, namely grand mean, linear, quadratic and cubic and include emotional valence as a control variable.

```
M_poly_3 <- stan_glm(mean_resp ~ valence + poly(humLike, 3),
                data = BA21_agg)

M_poly_2 <- stan_glm(mean_resp ~ valence + poly(humLike, 2),
                data = BA21_agg)

M_poly_1 <- stan_glm(mean_resp ~ valence + poly(humLike, 1),
                data = BA21_agg)

M_poly_0 <- stan_glm(mean_resp ~ 1 + valence,
                data = BA21_agg)

clu(M_poly_3)
```

Table E4

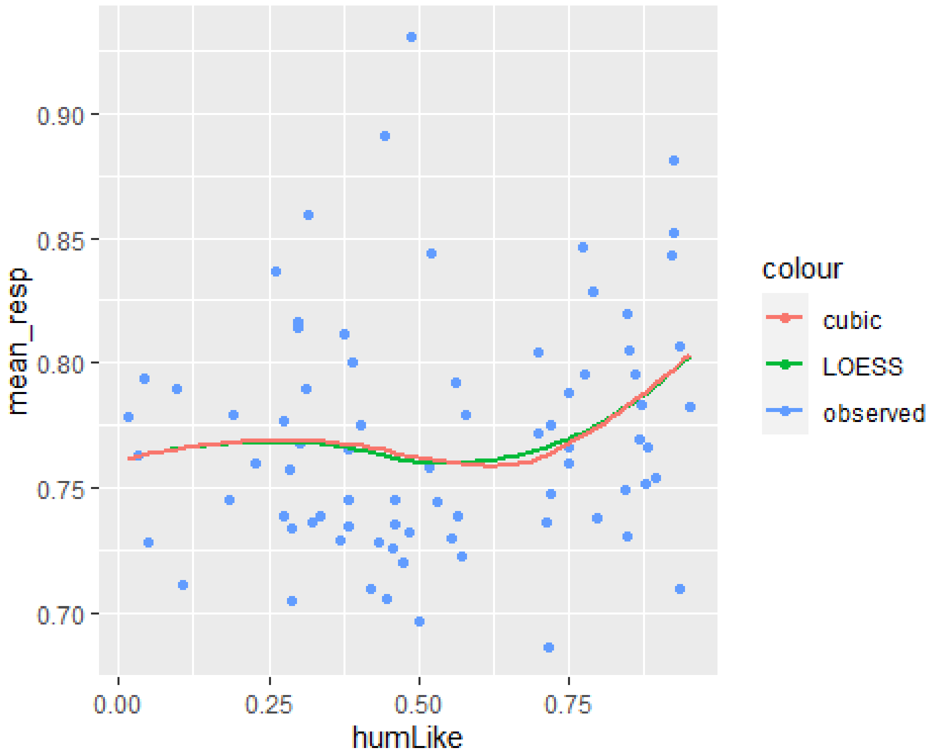
Parameter estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	0.5760378	0.5110060	0.6426081
poly(hum_like, 3)1	poly(hum_like, 3)1	0.5122479	0.0501577	0.9618364
poly(hum_like, 3)2	poly(hum_like, 3)2	0.2039400	-0.2525294	0.6671140
poly(hum_like, 3)3	poly(hum_like, 3)3	-0.0764050	-0.4945528	0.3797763
sigma_resid	NA	0.2275051	0.1880630	0.2830139

```
PP_poly_3 <- post_pred(M_poly_3)

PP_poly_3 %>%
  predict() %>%
  left_join(BA21_agg, by = "Obs") %>%
  ggplot(aes(x = humLike)) +
  geom_point(aes(y = mean_resp, color = "observed")) +
  geom_smooth(aes(y = mean_resp, color = "LOESS"), se = F) +
  geom_smooth(aes(y = center, color = "cubic"), se = F)

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

Figure E3

Plot visualising the cubic model, the LOESS model and the observed values.



Model selection

We use the leave-one-out (LOO) approximation to acquire and compare the relative predictive accuracy of all four population-level models.

```
Loo_poly <-
  list(loo(M_poly_0),
       loo(M_poly_1),
       loo(M_poly_2),
       loo(M_poly_3))

compare_IC(Loo_poly)
```

Table E5

Polynomials ranked by their predictive accuracy (LOO-IC)

Model	IC	Estimate	SE	Diff_IC
M_poly_1	looic	-268.6983	12.24563	0.0000000
M_poly_0	looic	-268.1633	12.19914	0.5350387
M_poly_2	looic	-266.5040	13.08301	2.1943270
M_poly_3	looic	-264.3055	13.12711	4.3928425

We can see that the cubic model is not the preferred one on population level, as one might expect for the uncanny valley effect. However, in the later steps of analysis we will observe that individual differences distort the graph on population level. Therefore, we use the cubic model to create a test statistic on the MCMC samples to give us the probability of obtaining an uncanny valley curve on population level.

```
P_wide <-
  posterior(M_poly_3) %>%
  as_tibble() %>%
  filter(type == "fixef") %>%
  select(chain, iter, fixef, value) %>%
  pivot_wider(id_cols = c("chain", "iter"),
              names_from = fixef,
              values_from = value) %>%
  mutate(shoulder = uncanny::shoulder(.[3:6]),
         trough = uncanny::trough(.[3:6]),
         is_uncanny = !is.na(shoulder) & !is.na(trough))

cat("The probability of the population level being a UV curve is: ",
mean(P_wide$is_uncanny))

## The probability of the population level being a UV curve is:  0.6315
```

Multilevel model

```
M_poly_4 <-
  stan_glmer(response ~ 1 + valence + humLike + humLike_2 + humLike_3 +
             (1 + valence + humLike + humLike_2 + humLike_3|Part),
             data = BA21)

PP_poly_4 <- post_pred(M_poly_4, thin = 5)

fixef_ml(M_poly_4)
```

Table E6

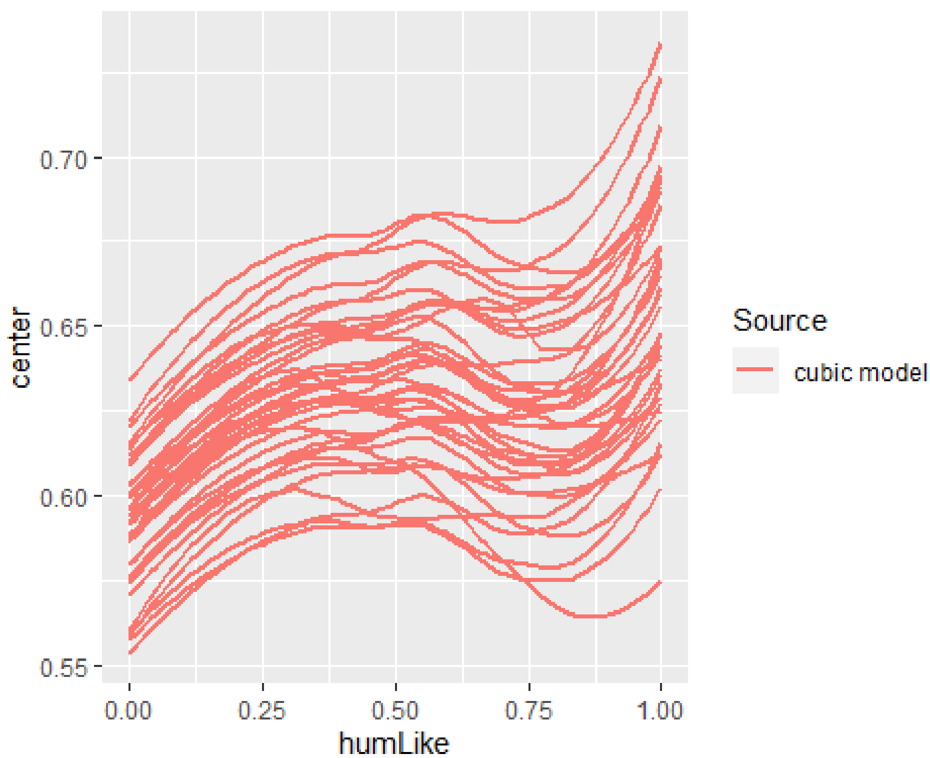
Population-Level Coefficients With Random Effects Standard Deviations

fixef	center	lower	upper	SD_Part
Intercept	0.5833803	0.5583426	0.6080007	0.0265205
valence	0.0011061	0.0009101	0.0012908	0.0002134
humLike	0.4778191	0.3051359	0.6479144	0.0179322
humLike_2	-1.1130629	-1.4843434	-0.7271630	0.0235903
humLike_3	0.7180369	0.4709761	0.9552268	0.0236564

```
PP_poly_4 %>%
  predict() %>%
  left_join(BA21, by = "Obs") %>%
  ggplot(aes(x = humLike)) +
  geom_smooth(aes(y = center, color = "cubic model",
                  group = Part), se = F) +
  labs(color = "Source")

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

Figure E4

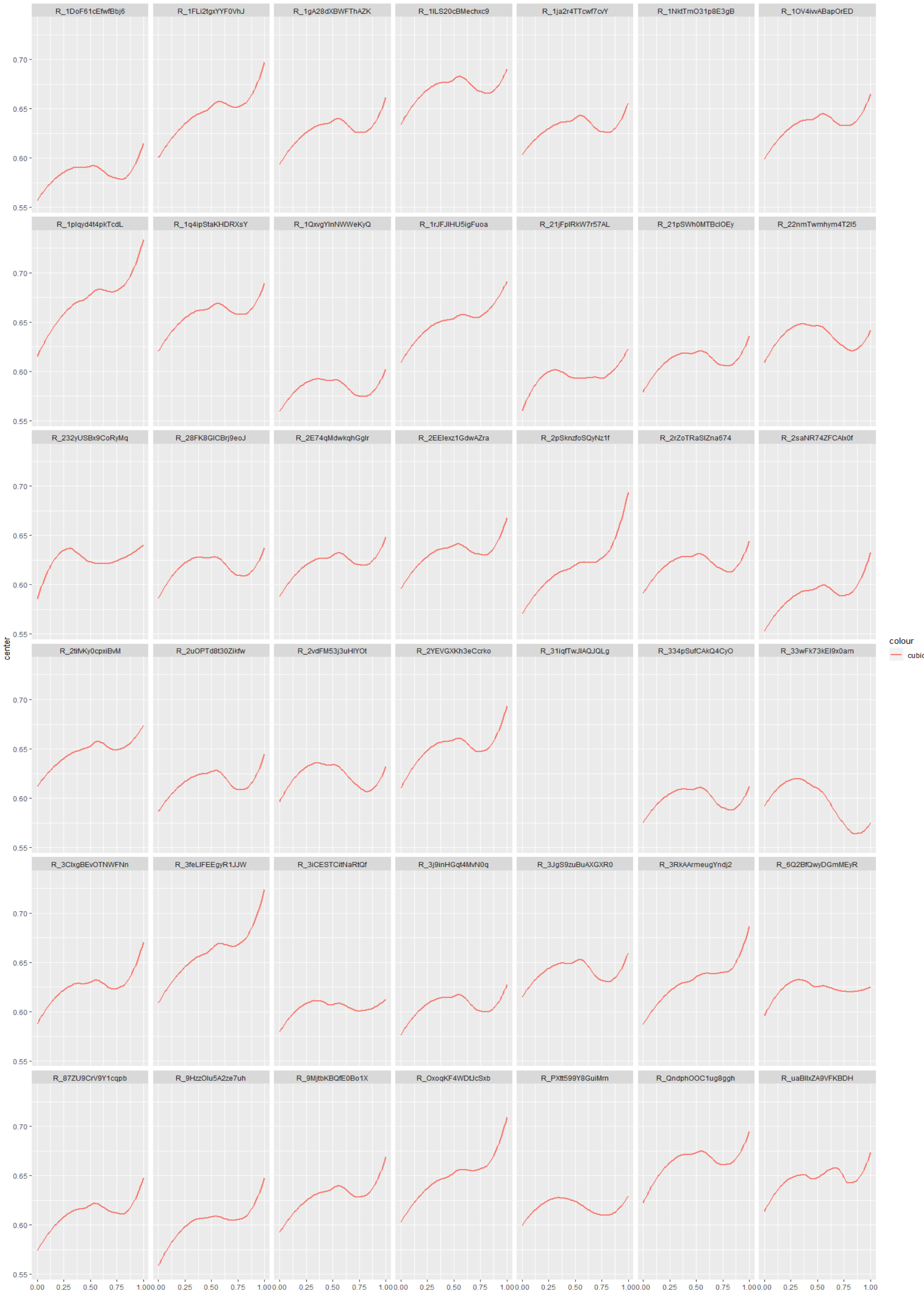
Spaghetti Plot of Multilevel Model with Individual Uncanny Valley Curves



```
PP_poly_4 %>%
  predict() %>%
  left_join(BA21, by = "Obs") %>%
  ggplot(aes(x = humLike)) +
  facet_wrap(~Part) +
  #geom_point(aes(y = response, color = "observed")) +
  #geom_smooth(aes(y = response, color = "LOESS"), se = F) +
  geom_smooth(aes(y = center, color = "cubic",
                  group = Part), se = F)

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

Figure E5

Individual Curves Using the 4th Degree Polynomial Model



Distributional Beta regression

```
M_poly_5 <-
  brm(bf(response ~ 1 + valence + humLike + humLike_2 + humLike_3 +
           (1 + valence + humLike + humLike_2 + humLike_3|Part),
                 phi ~ 1 + (1 | Part)),
             family = Beta(),
             data = BA21,
      inits = "0")

PP_poly_5 <- post_pred(M_poly_5, thin = 5)

P_poly <- posterior(M_poly_5)

fixef_ml(M_poly_5)
```

Table E7

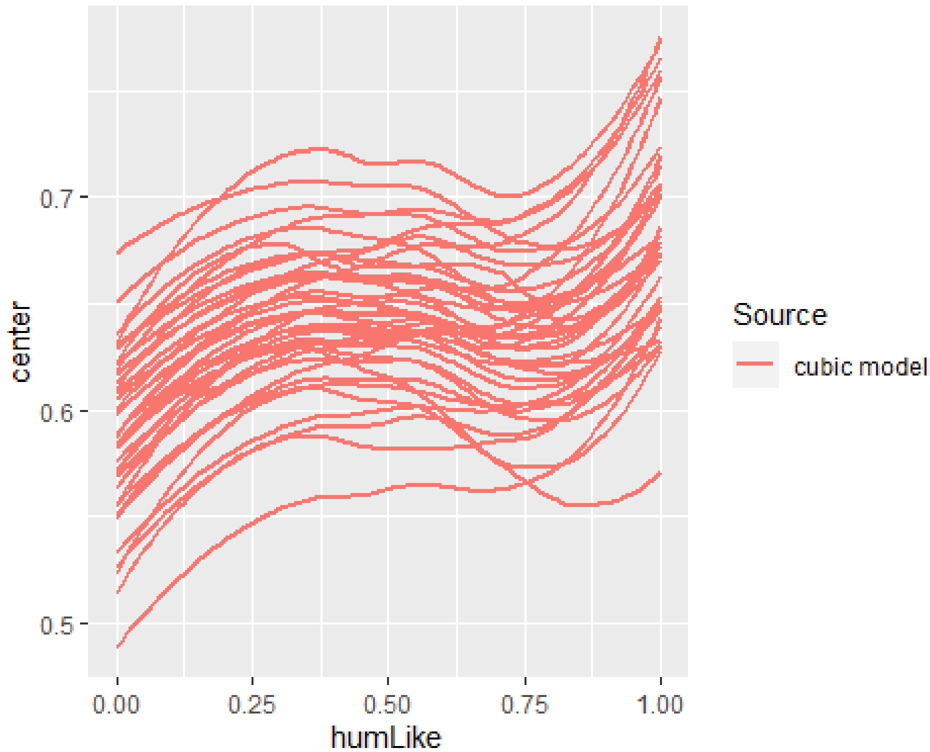
Population-Level Coefficients with Random Effects Standard Deviations

fixef	center	lower	upper	SD_Part	
Intercept	0.2423457	0.1349185	0.3537239	0.1725790	NA
NA	1.2259843	1.0541065	1.4012498	NA	0.5545595
valence	0.0035227	0.0026571	0.0044081	0.0012479	NA
humLike	2.1916328	1.4888111	2.8686954	0.1213779	NA
humLike_2	-5.0889238	-6.6040510	-3.5435657	0.1514233	NA
humLike_3	3.3125477	2.3226758	4.2920712	0.1318868	NA

```
PP_poly_5 %>%
  predict() %>%
  left_join(BA21, by = "Obs") %>%
  ggplot(aes(x = humLike)) +
  geom_smooth(aes(y = center, color = "cubic model",
                  group = Part), se = F) +
  labs(color = "Source")

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

Figure E6

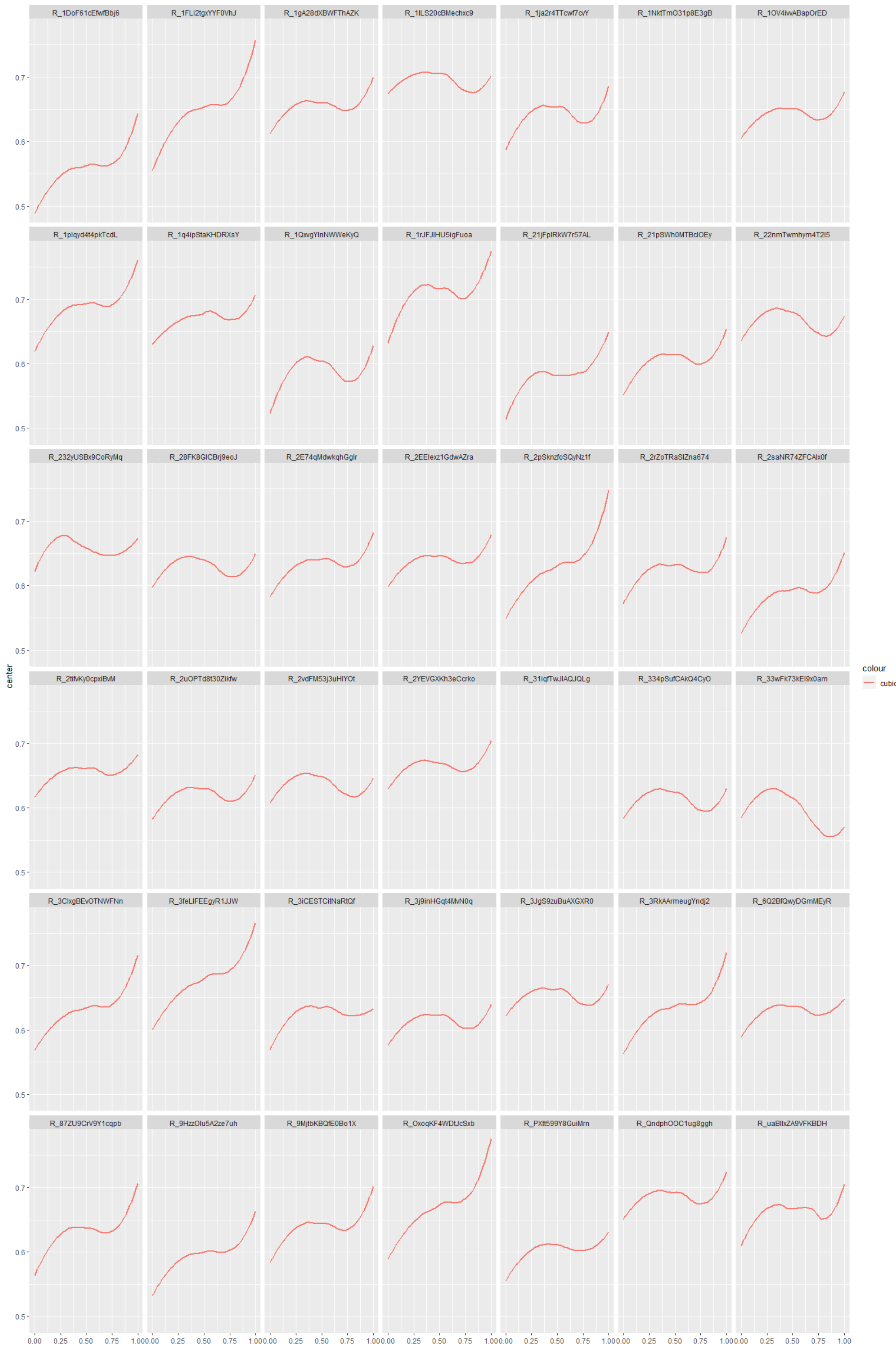
Spaghetti Plot of Multilevel Model with Distributional Beta Regression




```
T_predicted <-
  PP_poly_5 %>%
  predict() %>%
  right_join(BA21, by = "Obs")


T_predicted %>%
  ggplot(aes(x = humLike)) +
  facet_wrap(~Part) +
  #geom_point(aes(y = response, color = "observed")) +
  #geom_smooth(aes(y = response, color = "LOESS"), se = F) +
  geom_smooth(aes(y = center, color = "cubic",
                  group = Part), se = F)

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

Figure E7

Individual Curves Using the 5th Degree Polynomial Model



```
write_csv(T_predicted, file = "T_predicted.csv")
```

Universality

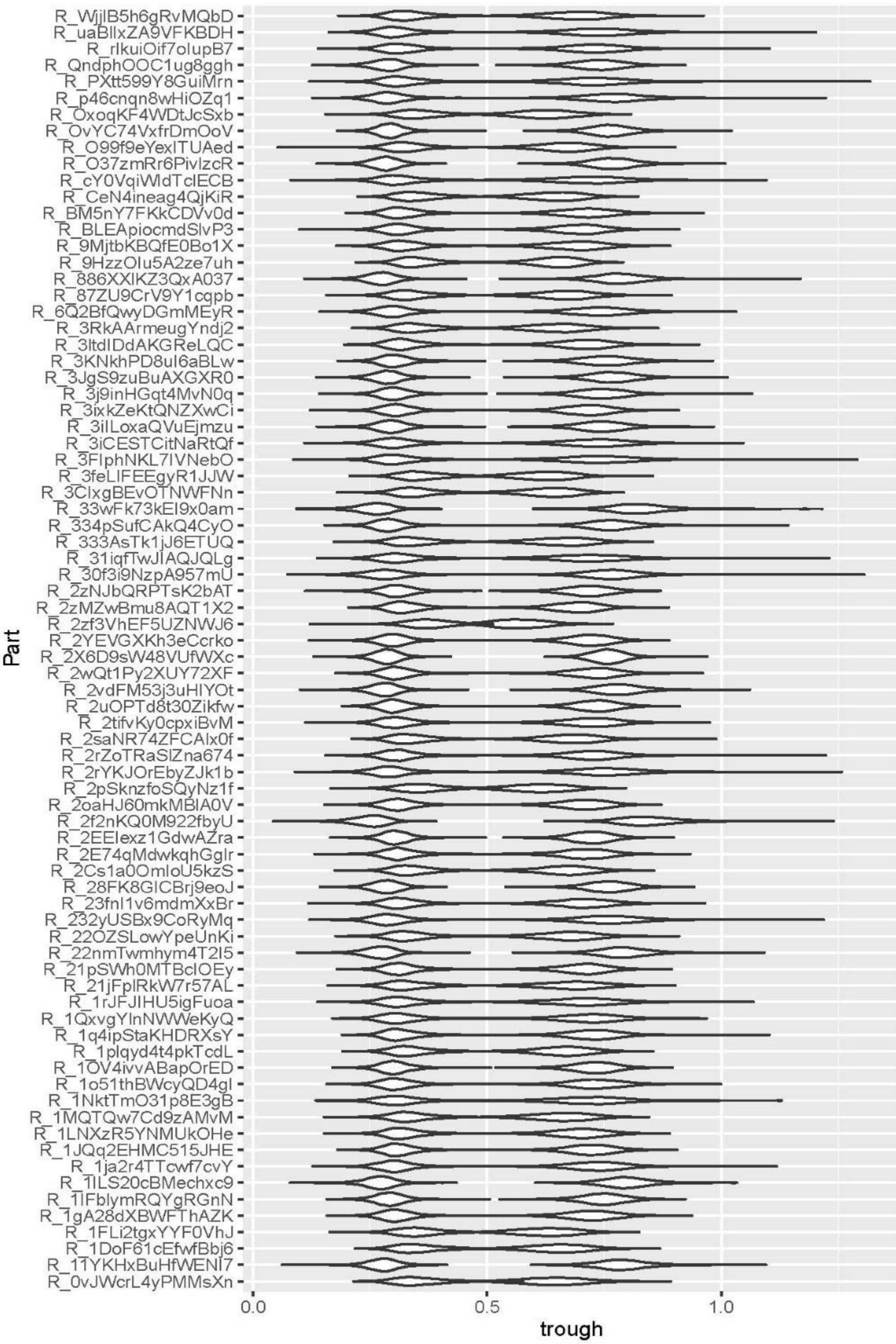
```
P_univ_uncanny <-
  posterior(M_poly_5) %>%
  #as_tibble() %>%
  dplyr::filter(is.na(nonlin), fixef != "valence") %>%
  re_scores() %>%
  select(iter, Part = re_entity, fixef, value) %>%
  tidyr::spread(key = "fixef", value = "value") %>%
  select(iter, Part,
         humLike_0 = Intercept,
         humLike_1 = humLike, humLike_2, humLike_3) %>%
  mutate(
    trough = trough(select(., humLike_0:humLike_3)),
    shoulder = shoulder(select(., humLike_0:humLike_3)),
    has_trough = !is.na(trough),
    has_shoulder = !is.na(shoulder),
    shoulder_left = trough > shoulder,
    is_uncanny = has_trough & has_shoulder & shoulder_left
  )

P_univ_uncanny %>%
  select(Part:shoulder) %>%
  pivot_longer(humLike_0:shoulder,
               names_to = "parameter",
               values_to = "value") %>%
  group_by(Part, parameter) %>%
  summarize(center = median(value, na.rm = T)) %>%
  pivot_wider(names_from = "parameter",
              values_from = "center") %>%
  write_csv(file = "Participant_level.csv")
```

Individual positions of shoulder and trough

```
P_univ_uncanny %>%
  ggplot(aes(x = Part)) +
  geom_violin(aes(y = trough, color = "Trough")) +
  geom_violin(aes(y = shoulder, color = "Shoulder")) +
#  theme(axis.text.x = element_text(angle = 90)) +
  coord_flip()
```

Figure E8

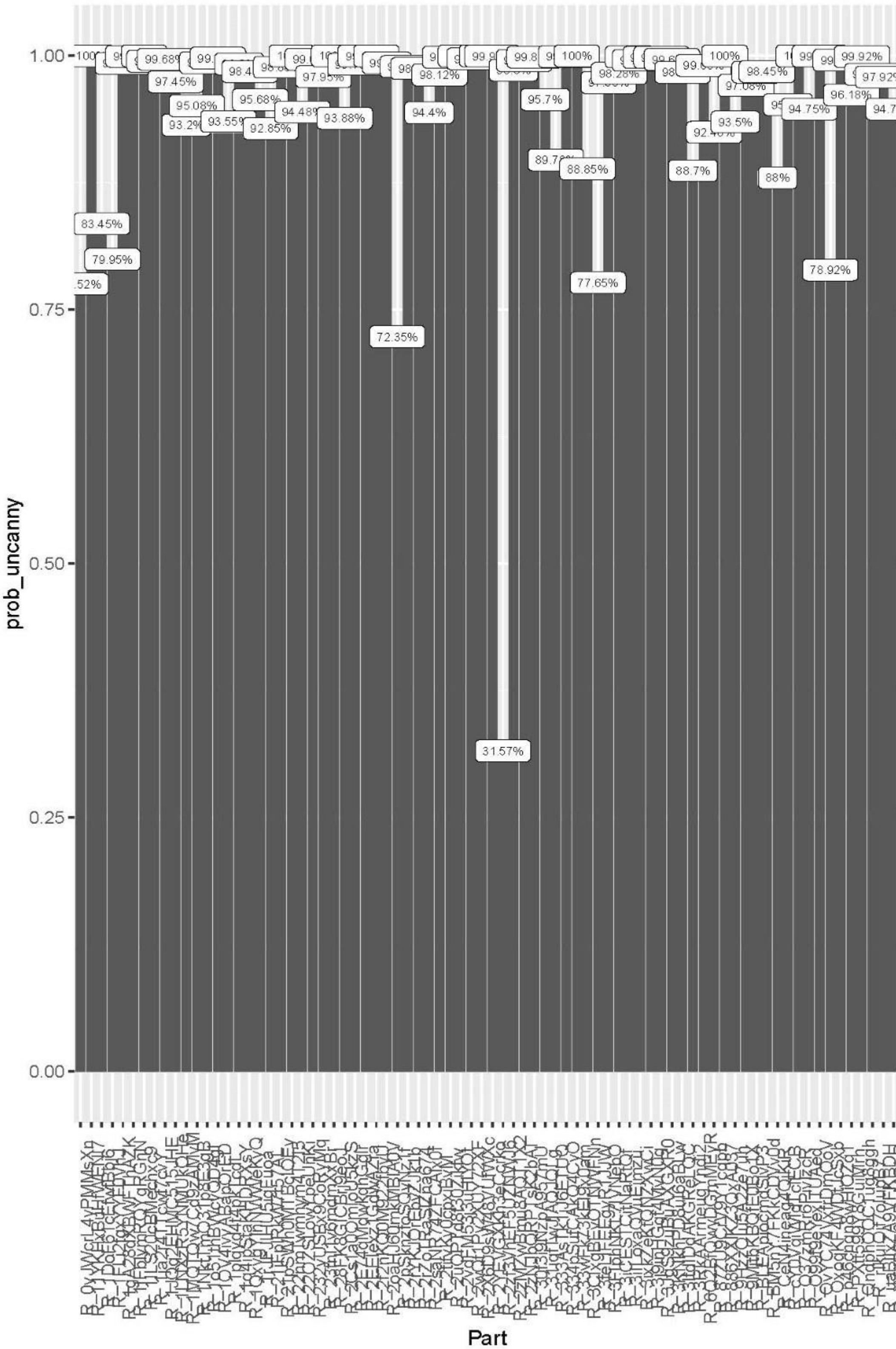
Violin Graph Displaying Position of Shoulder and Trough for Every Participant's Curve



```
P_univ_uncanny %>%
  group_by(Part) %>%
  summarize(prob_uncanny = mean(is_uncanny, na.rm = T)) %>%
#  ungroup() %>%
#  mutate(Part_ord = rank(prob_uncanny)) %>%
  mutate(label = str_c(100 * round(prob_uncanny, 4), "%")) %>%
  ggplot(aes(x = Part, y = prob_uncanny)) +
  geom_col() +
  geom_label(aes(label = label), size = 2) +
  theme(axis.text.x = element_text(angle = 90))
```

Figure E9

Histogramme of Individual Probabilities for Obtaining an Uncanny Valley Curve per Participant



```
save(BA21, BA21_agg, PP_poly_4, M_poly_4, P_univ_uncanny, M_poly_3,
     PP_poly_3, M_poly_2, M_poly_1, M_poly_0, Loo_poly, M_poly_5, PP_poly_5,
     P_univ_uncanny, M_6, M_7,
     file = "Bachelor thesis Uncanny Valley.Rda")
```