Human-like Robots and the Uncanny Valley:

A Meta-Analysis of User Responses Based on the Godspeed Scales

Martina Mara[1], Markus Appel[2], and Timo Gnambs[3]

[1] Johannes Kepler University Linz, Austria

[2] University of Würzburg, Germany

[3] Leibniz Institute for Educational Trajectories, Germany

Correspondence concerning this article should be addressed to Martina Mara, Johannes Kepler University Linz, Altenberger Straße 69, 4040 Linz, Austria, E-mail: martina.mara@jku.at.

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Author Note

Martina Mara https://orcid.org/0000-0003-3447-0556

Markus Appel https://orcid.org/0000-0003-4111-1308

Timo Gnambs https://orcid.org/0000-0002-6984-1276

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Abstract

In the field of human-robot interaction, the well-known uncanny valley hypothesis proposes a curvilinear relationship between a robot's degree of human likeness and the observers' responses to the robot. While low to medium human likeness should be associated with increasingly positive responses, a shift to negative responses is expected for highly anthropomorphic robots. As empirical findings on the uncanny valley hypothesis are inconclusive, we conducted a random-effects meta-analysis of 49 studies (total $N = 3,556$) that reported 131 evaluations of robots based on the Godspeed scales for anthropomorphism (i.e., human likeness) and likability. Our results confirm more positive responses for more human-like robots at low to medium anthropomorphism, with moving robots rated as more human-like but not necessarily more likable than static ones. However, because highly anthropomorphic robots were sparsely utilized in previous studies, no conclusions regarding proposed adverse effects at higher levels of human likeness can be made at this stage.

Keywords: uncanny valley, humanoid robot, anthropomorphism, likability, meta-analysis

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1. Introduction

When people think of robots, they usually have an image of a human-like machine in their minds. An apparatus with arms, legs and a head, covered in metal or possibly silicone skin (cf. Cave et al., 2020; Mara et al., 2020). Even though such robots hardly, if at all, exist in our everyday lives, media reports about engineering advancements and science fiction stories about the—sometimes more, sometimes less peaceful—relationship between humans and their robotic counterparts have long made us wonder what it would be like if humanoid machines were really among us. Given the diffuse mental pictures many people have about robots, representative survey data show that many people are skeptical regarding their use in everyday life (e.g., Gnambs, 2019; Gnambs & Appel, 2019). One of the most popular conceptual frameworks to speculate about human responses to human-like robots is the uncanny valley hypothesis (Mori, 1970). Its central proposition is that increasing anthropomorphism (i.e., human likeness) in artificial characters does not necessarily go hand in hand with increasing likability, but will result in negative responses when the degree of human resemblance is very high, yet not perfect. Over the past decade, the number of empirical investigations of human-robot relationships and determinants of robot acceptance has steadily increased, many of which have dealt with potentially aversive reactions to human-like machines. However, due to inconsistent empirical evidence, the existence of the uncanny valley effect and the conditions under which it is more or less pronounced are a matter of debate (cf. Kätsyri et al., 2015; Wang et al., 2015; Zhang et al., 2020). Given the great popularity of the uncanny valley hypothesis, it is surprising that its basic propositions still lack systematic empirical corroboration. We address this gap by conducting the first

meta-analytic test of the curvilinear relationship between the human likeness and the likability of robots as proposed by Mori (1970).

1.1 Human-Like Robots

From mythological figures such as the Golem to modern-day science fiction, stories about artificial replications of the human species were told throughout history. Starting in the 18th century, there have also been attempts to physically create human-like machines. Around the first industrial revolution, watchmakers and mechanical engineers constructed life-sized automatons in the shape of adult humans that appeared as if they could write, draw, or play chess (cf. Voskuhl, 2013). When the term "robot" was first ever used in the context of the 1920 theater play "Rossum's Universal Robots" (Čapek, 1920/2001), it was also human-like automata that were shown on stage. Today, the imitation of the human body and mind constitutes an objective that is being pursued in subdisciplines of robotics and artificial intelligence. While the number of functional human-like robots is still quite small to date, some robotics labs specialize in developing human-like autonomous machines that can serve entertainment purposes (Johnson et al., 2016), answer questions to customers (Pandey & Gelin, 2018), facilitate telepresence (Ogawa et al., 2011), assist in healthcare (Yoshikawa et al., 2011), act as sex toys (Döring et al., 2020), or are used for research into human behavior and bodily functions (Hoffmann & Pfeifer, 2018). Depending on how easily they can be distinguished from real people, human-like robots are typically referred to either as *humanoids* or *androids*. Humanoid robots are easily recognized as robots by their overall mechanical look, even though they usually possess a head, torso, arms, and sometimes legs. In contrast, android robots are intended to mimic human appearance as realistically as possible, emphasized for example by silicone skin, clothing, wigs, or highly realistic details such as eyelashes (cf. Ishiguro, 2016).

1.2 The Uncanny Valley Hypothesis

Many years before robotics could even draw near the development of real android robots, Japanese roboticist Masahiro Mori introduced the hypothetical model of the uncanny valley (Mori, 1970). Initially intended more as a philosophical contribution than a blueprint for empirical research, after many years of little attention, the uncanny valley turned into a much-discussed and much-studied concept in the past two decades. The popular uncanny valley graph (Figure 1), which was originally based only on Mori's personal experience and conjecture, proposes a nonlinear relationship between human likeness of an artificial figure, for example of a robot, and the valence it elicits in observers. Mori suggested that within a spectrum of a generally low to medium degree of visual anthropomorphism, increasing levels of human likeness are associated with increasing acceptance and likability. Observers should therefore sympathize more strongly with a slightly humanoid robot than, for example, with a swivel-arm robot from industry. However, after a first positive peak of the curve along the human likeness continuum, this effect should reverse as soon as a rather high level of nearly realistic human likeness is obtained. At this point, acceptance is expected to drop and the android should evoke a negative and irritating feeling of uncanniness (eeriness, creepiness). As an inherent property of animated entities, motion is moreover assumed to moderate the uncanny valley effect, with moving robots eliciting more pronounced reactions than static objects (or static pictures of moving objects). Therefore, a moving, highly human-like android robot should be perceived as less likable than the corresponding still artifact. Ultimately, on the right side of the uncanny valley, the likability curve is expected to go up again when a robot’s design is so perfectly realistic that it becomes indistinguishable from a real person. At the upper end of the human likeness continuum, at which the real human constitutes the end point, the valence of associated affect and cognition should then reach a second positive peak (Mori, 1970; Mori et al., 2012).

Different perceptual, cognitive, or evolutionary explanations have been proposed to underly the uncanny valley phenomenon, including assumptions related to categorical uncertainty, difficulties in the configural processing of humanlike artifacts, threat avoidance, or the role of android robots as salient reminders of human mortality (see Diel & MacDorman, 2021, and Wang et al., 2015, for an overview of suggested mechanisms).

1.3 Research on the Uncanny Valley

Compared to other scientific fields, research on the uncanny valley is characterized by a great diversity of involved disciplines, ranging from robotics, computer science, and virtual reality to animation, design, philosophy, communication science, and psychology. It therefore comes as no great surprise that the available studies exhibit considerable methodological heterogeneity. While, for example, a number of researchers investigated the uncanny valley by presenting study participants with physical humanoid or android robots (e.g., Bartneck, Kanda, et al., 2009; Mara & Appel, 2015) or with media representations of actually existent robots (e.g., Kim et al., 2020), other scholars focused on computer-generated stimuli such as virtual faces and avatars (e.g., Kätsyri et al., 2019; Stein & Ohler, 2017) or self-created image morphs (e.g., Lischetzke et al., 2017). Independent of the visual appearance of robots, a more recent branch of uncanny valley research also deals with aversive reactions to purely behavioral human likeness, partly relying on textual descriptions of robots as stimuli (e.g., Appel et al., 2020). Different approaches also prevail in the operationalization of central variables and associated measurements. Single-item self-reports appear to be a common means in research on user responses to human-like robots. Regarding validated multi-item scales for investigations of the uncanny valley it is in particular the Godspeed questionnaire by Bartneck, Kulić, et al. (2009) that can be regarded a dominant instrument for the assessment of robot anthropomorphism (representing the x-axis in Figure 1) and robot likability (representing the y-axis in Figure 1) (cf. Weiss & Bartneck, 2015). Another multi-

item measure, the uncanny valley indices by Ho and MacDorman (2010, 2017), has been utilized in rather few studies so far.

Empirical support for the idea of the uncanny valley itself has been inconsistent. While results from some studies provide evidence for Mori's propositions (e.g., Mathur & Reichling, 2016) or found partial support (e.g., Bartneck et al., 2007), others failed to reveal a drop in acceptance for highly anthropomorphic machines (e.g., Bartneck, Kanda, et al., 2009) or even revealed an additional uncanny valley along the human likeness continuum (Kim et al., 2020). A literature review (Kätsyri et al., 2015) concluded that a bulk of studies supported a linear increase in affinity for more human-like robots, while evidence for nonlinear uncanny valley effects was scarce. Similarly, the assumption that robot motion should result in stronger uncanny valley effects (see Figure 1) was rarely corroborated (Piwek et al., 2014; Thompson, et al., 2011). So far, a quantitative summary of uncanny valley effects is sorely missing.

1.4 The Present Study

One factor that contributes to the heterogeneity of study results on the uncanny valley might be the use of unstandardized measurements of the core constructs that exhibit unknown reliability and validity (cf. Wang et al., 2015). Therefore, the present meta-analysis focuses on the multi-item Godspeed questionnaire (Bartneck, Kulić, et al., 2009) that constitutes a widely used instrument for the assessment of both anthropomorphism and likability in human-robot interaction research. It can be used to map values on both the x-axis and the y-axis of the uncanny valley graph. In the interest of ecological validity, we furthermore decided to only include studies in which participants were presented with actual robotic systems or media representations of such. To examine the central propositions of the uncanny valley effect as suggested by Mori (1970) in Figure 1, we hypothesized that (a), overall, with increasing

human likeness attributed to a robot, it will be rated more positively (i.e., higher likability).[1] Moreover, (b) the association between human likeness and likability should show a nonlinear relationship, leading to (c) an inverted U-shaped function and thus a sharp decline of likability ratings for highly but not perfectly anthropomorphic robots. Furthermore, (d) a second turning point at the end of the inverted U-shape at the bottom of the valley was expected to lead to more positive ratings for the most human-like robotic agents that are (nearly) indistinguishable from humans. Finally, we assumed (e) robot motion to have a moderating role because Mori (1970) speculated that motion, as an inherent property of animated objects, should amplify the uncanny valley effect.

2. Method

2.1 Literature Search and Study Selection

In January 2021, we performed a literature search for studies in which at least one robot was evaluated with the help of the Godspeed questionnaire by identifying articles in Google Scholar citing Bartneck, Kulić, et al. (2009). Initial search results provided 1,330 potentially relevant publications. After screening the titles, abstracts, and method sections of these articles, 95 records were subjected to detailed evaluations. To be included in the meta-analysis, a study had to meet the following criteria. First, it had to have administered the anthropomorphism and likability scales of the Godspeed questionnaire, without substantial changes to the item content. However, we considered short forms of the scale if they included at least two items and we allowed for deviations in the number of response options (from the original five-point ratings). Second, the respondents interacted with or viewed a real robot, a close reproduction of a real robot, or viewed a photograph or video of a robot. Virtual agents, avatars, morphed images, fictional representations (e.g., drawings, caricatures), or mere verbal

[1] Nonlinear prediction models such as the Uncanny Valley hypothesis might exhibit an average linear trend, which is then specified in detail by nonlinear associations between the focal variables.

descriptions of robots were not considered. No restrictions were applied on the size or the form of the robot to cover technical systems with a broad range of human likeness. Third, the study must have reported means, standard deviations, and sample sizes for both scales or provided information to derive these statistics (e.g., plots). Fourth, the study must have included healthy samples without psychological disorders. Finally, we acknowledged all studies published until December 2020. No restrictions were set on the publication type. After applying these criteria, 49 publications reporting on 93 independent samples were available (see the flow diagram in the supplemental material).

2.2 Data Extraction

From each article, we coded the mean, standard deviation, reliability (coefficient alpha), number of administered items, and number of response options for the anthropomorphism and likability scales. For 19 studies that did not report numeric results, means and standard deviations were approximated from plots (e.g., histograms with standard errors) using the *R* package *metaDigitise* version 1.0.1 (Pick et al., 2019). In case a study reported on multiple robots, we coded each robot separately. In contrast, if different ratings were presented for the total sample and different subgroups (e.g., different experimental conditions), we only coded the results for the total sample (i.e., with the largest sample size). However, if information was available for different values of the examined moderators (see below), then results for the different subgroups (i.e., whether the robot moved or talked) were coded separately. Additionally, we recorded the name of the evaluated robot, how it was presented (real, photo, video, virtual reality), whether it moved, and whether it communicated (e.g., talked or made sounds). Descriptive information on the sample included the sample size, the mean age of the respondents, the share of females, the country of origin of the participants, and the language of administration. Finally, we noted the publication year and the publication type (journal, proceedings, book chapter, thesis) of each study. All studies were coded by the last author and, independently, by three research assistants. Additionally,

the risk of bias for each study was evaluated by two research assistants using eight items of the *Risk of Bias Utilized for Surveys Tool*, a checklist to code quality criteria such as the acceptability of exclusion rates or the sufficiency of sample sizes for primary studies used in meta-analyses (Nudelman & Otto, 2020).

For most coded variables, the interrater reliability (Krippendorff's alpha) indicated good agreement exceeding $\alpha_K \geq .85$ (*Mdn* = .90). However, the codings of the sample sizes ($\alpha_K = .63$) and whether the robot moved ($\alpha_K = .31$) or communicated ($\alpha_K = .66$) were less consistent. The interrater reliability of the risk of bias assessments was good with $\alpha_K = .91$. Discrepancies were solved by the first author. The characteristics of the samples including the coded statistics are summarized in the supplemental material.

2.3 Analysis Plan

Because the uncanny valley hypothesis refers to a nonlinear association between anthropomorphism and likability, the means of the likability scale were the focal statistics that were pooled across studies. A random-effects meta-analysis was conducted using the *metafor* software version 2.4-0 (Viechtbauer, 2010) with a restricted maximum likelihood estimator. To account for sampling error, the means were weighted by the inverse of their sampling variances. Because some studies reported more than one evaluation (e.g., obtained for different robots), we estimated a three-level meta-analytic model that acknowledged dependencies between samples using a random-effects structure (cf. Cheung, 2019; Van den Noortgate et al., 2013). The uncanny valley effect was examined using polynomial meta-regression analyses that predicted likability ratings from anthropomorphism scores. To model the hypothesized inflection points (see Figure 1) the regression also included higher-order polynomials of the anthropomorphism scores. In sensitivity analyses, we included several additional covariates (e.g., share of female respondents, risk of bias) and repeated the polynomial regression to determine the robustness of the observed effects. Moreover, we also repeated these analyses excluding outliers (Viechtbauer & Cheung, 2010) and using robust

meta-regression analyses (Hedges et al., 2010) to highlight the generalizability of results against different methodological choices (cf. Voracek et al., 2019). The homogeneity of the pooled scores was tested using the χ^2-distributed Q-statistic and quantified using I^2 that indicates the percentage of the total variance in observed scores due to random variance. Moderators were evaluated using the χ^2-distributed omnibus test statistic Q_m. The precision of the predicted nonlinear association between anthropomorphism and likability was determined using a 95% confidence interval. All analyses were conducted in *R* version 4.03 (R Core Team, 2020).

2.4 Open Practices

The checklist for the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (Page et al., 2021) is provided in the supplemental material. To foster transparency and reproducibility, we also provide the coding manual, extracted data, computer code, and analyses results at https://osf.io/t9rdk. The meta-analysis was not preregistered.

3. Results

3.1 Description of Meta-Analytic Database

The meta-analytic database included 49 studies that reported on 93 independent samples and included 131 evaluations of robots. Each sample contributed between 1 and 9 (*Mdn* = 1) evaluations of a robot using the Godspeed scales, predominantly in their original form including five items and five-point response scales. Both scales exhibited good reliabilities with median coefficient alphas of .86 for anthropomorphism and .89 for likability. Results of respective reliability generalizations are summarized in the supplemental material. Key characteristics of the included samples are also given in Table 1. The sample sizes ranged from 6 to 121 and included a median of 21 respondents. Most samples were from Germany (44%) and the United Kingdom (11%). The median proportion of female participants was 50%. Although the mean age of the samples spanned a broad range from 9 to 68 years, most samples were rather young (*Mdn* = 25 years) and dominated by students or university

personnel (79%). Few studies included more diverse groups such as individuals with lower education (Trovato et al., 2015b), children (Meghdari et al., 2018; Shariati et al., 2018), or senior citizens (Rosenthal-von der Pütten et al., 2017). About 55% of studies were published in conference proceedings, while journal articles (33%) were less prevalent. The risk of bias assessments had a median of 3 (on a scale from 0 to 8) and, thus, indicated that many studies exhibited several design or reporting weaknesses that might have limited the validity of the reported study results to some degree.

3.2 Evaluations of Robots

The studied robots came in different forms and sizes representing a broad range of different models. Most available ratings pertained to the NAO robot by SoftBank Robotics (33%), the iCub robot by the Italian Institute of Technology (8%), and the Pepper robot by SoftBank Robotics (7%). In addition, various custom-built robots were examined, such as the bartender robot JAMES (Foster et al., 2012; Giuliani et al., 2013), the neuro-inspired companion robot NICO (Kerzel et al., 2020), the blessing robot BlessU2 (Löffler et al., 2019), a Sunflower housing robot (Syrdal et al., 2013), or the industrial robot ARMAR-6 (Busch et al., 2019). The distributions of the average anthropomorphism and likability scores for these robots in Figure 2 highlight two intriguing results. First, the observed anthropomorphism scores ranged between 1.20 and 4.14, and most ratings fell in the lower middle range of possible scores (*Mdn* = 2.61). Thus, human likeness scores in the upper range were scarce. Second, the observed likability scores ranged between 2.63 and 4.98 (*Mdn* = 3.92). This implies that most robots were rated moderately to very favorably, whereas only a few likability ratings were in the low range.

However, there were notable differences in these evaluations between different robot models. Therefore, we pooled the anthropomorphism and likability scores for selected robot models and summarized the meta-analytic estimates in Figure 3. Detailed meta-analytic results, based on calculations in which we used the robot model as a predictor in a meta-

regression, are reported in the supplemental material. For example, the bartender robot JAMES was rated significantly ($p < .05$) less human-like as compared to the average rating across all robots. In contrast, the iCub robot and Pepper received significantly higher anthropomorphism scores (see Table S2). A rather similar picture emerged for the pooled likability ratings. While the bartender robot JAMES was evaluated significantly less likable as compared to the average evaluation, the NAO robot was evaluated significantly more likable. Interestingly, the robot model explained about 20% in anthropomorphism scores, while it only accounted for about 4% in likability ratings.

3.3 Tests of the Uncanny Valley Hypothesis

The association between the two Godspeed scales was examined using meta-regression analyses that predicted the likability scores from the anthropomorphism ratings. The nonlinear relationship suggested by the uncanny valley hypothesis (see Figure 1) could be modeled using higher-order polynomials of degree 3. To empirically determine the optimal number of higher-order terms, different meta-regression models were estimated and compared using the Bayesian information criterion (Schwarz, 1978). This suggested the inclusion of a linear term, a quadratic term, and a cubic term (see supplemental material). The respective meta-regression revealed a significant ($p < .05$) effect for anthropomorphism ($Q_m = 89.46$, $df = 3$, $p < .001$) that explained about 5% in the variance of likability ratings between samples (see Table 2). These results were rather robust ($Q_m = 98.43$, $df = 3$, $p < .001$) and replicated after controlling for sample characteristics (i.e., mean age, share of women, publication year, country), robot characteristics (i.e., movement, communication), and methodological characteristics (i.e., presentation mode, risk of study bias). To study the effect in more detail the likability ratings predicted from this meta-regression model (including a 95% confidence interval) were plotted in Figure 4. Consistent with assumption (a), these results confirmed more positive evaluations for more human-like robots overall. In accordance with assumption (b), we also found evidence for a nonlinear effect. Although the effect approximated a

sigmoid shape with a plateau in the region of the greatest anthropomorphism scores contained in the sample, we were unable to corroborate the hypothesized decline of likability for highly realistic android robots as stated in assumption (c). Consequently, we were also unable to identify the rise of likability at even higher scores of human likeness as expected in assumption (d). Again, these results were rather stable and replicated after controlling for various covariates (see Figure 4 and Table 2). The pooled association between anthropomorphism and likability was also rather invariant towards various methodological choices and replicated after excluding outliers, children, or older samples and adopting robust meta-analytic models (see supplemental material).

3.4 Movement and Other Moderating Effects

In line with Mori's hypothesis (Mori et al., 2012), static robots were evaluated significantly less human-like as compared to moving robots (B = -0.35, 95% CI [-0.56, -0.14]). In contrast, movement had no impact on likability ratings (see Table S2 in the supplemental material). Unexpectedly, communication had an opposite effect: For anthropomorphism, it was immaterial whether a robot was mute or communicated with the participants (B = 0.23, 95% CI [-0.07, 0.54]), whereas communicative robots were evaluated significantly ($p < .05$) more likeable as compared to mute robots (B = -0.27, 95% CI [-0.47, -0.06]). To examine whether these effects also extended to the nonlinear association between anthropomorphism and likability, we extended the previous meta-regression analyses and included respective interactions for the linear, quadratic, and cubic terms. However, inconsistent with assumption (e), these interactions were not significant (see Table 2), thus, indicating that movement and communication did not moderate the predicted effects given in Figure 4. However, our database included only 19 results with static robots, while most of the robots exhibited some form of movement.

4. Discussion

Masahiro Mori's (1970) hypothetical graph on the uncanny valley has developed into a dominant influence on recent research into user perceptions of human-like robots. Complementing and extending insights gained from narrative reviews on the uncanny valley hypothesis (Kätsyri et al., 2015; Wang et al., 2015; Zhang et al., 2020), we presented the first quantitative, meta-analytical review of the main assumptions underlying the uncanny valley effect. We focused on the characteristic relationship between user assessments of human likeness (the x-axis) and likability (the y-axis) that was proposed by Mori (1970, Figure 1), based on the Godspeed scales (Bartneck, Kulić, et al., 2009), a standard measure in the field (cf. Weiss & Bartneck, 2015). To this end, state-of-the-art meta-analytic methods that acknowledged dependencies between samples using a random-effects structure (cf. Cheung, 2019; Van den Noortgate et al., 2013) were used to study the nonlinear hypothesis with polynomial meta-regression analyses. From our quantitative assessment of the 93 independent samples that comprised our meta-analytic database, a main insight is the limited range of anthropomorphism and likeability scores in the examined primary studies (Figure 2). In the large majority of studies, the focal robot was experienced as being not quite human-like with means ranging below the scale's midpoint. Means above 3.5 on a 5-point scale were almost entirely missing. Likewise, and even more pronounced, the focal robots were experienced as highly likable on average in the primary studies. The large majority of studies reported mean likability scores above the midpoint of the scale. The limited range of the primary study scores is highly relevant for our main meta-analytic aim, gathering quantitative evidence for or against the uncanny valley hypothesis. According to Mori (1970) and contemporary interpretations of his ideas (e.g., Diel & MacDorman, 2021; Wang et al., 2015), the characteristic drop in likability is experienced at the higher end of the human likeness continuum. Based on the studies underlying our meta-analysis, this higher end of the human likeness continuum is unchartered territory.

We deduced several functional properties from the curvilinear explication of the uncanny valley hypothesis. Despite the identified limitations in scale range, likability scores supported the first assumption (a) derived from Mori's uncanny valley hypothesis in that increasing human likeness was found to be associated with increasingly positive user responses within the spectrum of low to medium anthropomorphism. Important against the backdrop of the uncanny valley literature and in line with assumption (b), our results also suggest a nonlinear effect, leading to a flattening of the likability curve at about 75% of the anthropomorphism scale range (x-axis). However, because hardly any robots had been rated as highly human-like in the available primary studies, neither assumption (c) that such robots would lead to a pronounced drop in acceptance nor assumption (d) that near-to-perfect copies of humans at the end of the continuum would lead to an ultimate grow in acceptance could be evaluated. Mori's core proposition about adverse effects of android robots can therefore neither be rejected nor confirmed at this stage.

We further examined several potential moderating variables. A comparison between static and moving robots was of particular relevance to the original uncanny valley hypothesis. Static robots were evaluated less human-like than moving robots but movement had no impact on likability ratings. Importantly, the linear, quadratic, and cubic associations between human likeness and likability did not differ significantly between statically presented robots and such that were moving. Assumption (e), based on Mori's description of a potentially intensifying role of robotic motion, therefore must be rejected in view of the current data.

4.1 Limitations and Implications

As outlined above, our quantitative test of the uncanny valley hypothesis is preliminary, as primary studies that captured high degrees of human likeness were missing. The low human likeness scores observed could be a function of several factors. First, the robotic platforms examined in the primary studies do not stipulate high human likeness (e.g., NAO

and similar designs, see supplemental material). Second, participants naïve to robotics may use expectations derived from science-fiction as a point of comparison (Appel et al., 2016; Mara & Appel, 2015). Due to the fact that the state of today's technological advancement rarely matches sci-fi worlds, robots examined in human-robot interaction research have to fall short compared to fictional robots. The original movie Blade Runner (Scott, 1982), for example, showed a world in the year 2019 in which humans and human-like robotic replicants mingled. Participants with high technological knowledge or even a study emphasis in computer science, in turn, may be aware of technological glitches or wizard-of-oz simulated interactions.

We deliberately restricted our study pool to primary studies that reported data on the Godspeed Scales (Bartneck, Kulić, et al., 2009) to achieve high comparability and to prevent an influx of data with low reliability or validity, which has been described as a substantial problem in the field (Wang et al., 2015). The Godspeed Scales are in particular widespread use, constituting one of the standard measures in the field. Despite their popularity, it should not be dismissed that the Godspeed Scales themselves have also faced some criticism in the past (Carpinella et al., 2017; Ho & MacDorman, 2010). For example, an exploratory factor analysis conducted by Carpinella and colleagues (2017) indicated low eigenvalues and low reliabilities for some of the five Godspeed components. However, this was mainly true for the animacy and safety scales, but not for anthropomorphism and likability. Consistent with this and in support of our decision to use the Godspeed Sales, our database showed high reliabilities for both the anthropomorphism scale and the likability scale. That said, future meta-analyses could apply more liberal inclusion criteria. Promising alternative measures include the scales by Ho and MacDorman (2010; 2017), which were developed specifically for research on the uncanny valley hypothesis, or the Robotic Social Attributes Scale (Carpinella et al., 2017), which assesses warmth and competence as components of social perception and discomfort as a potential measure for uncanny experience.

We further restricted our meta-analysis to genuine implementations of robotic systems. Studies that relied on verbal descriptions, drawings of robots, or morphed pictures (e.g., Lischetzke et al., 2017; MacDoman & Ishiguru, 2006) were excluded. Whereas these stimuli could arguably increase human likeness (e.g., morphs between robots and humans, Lischetzke et al., 2017), such stimuli have been criticized for lacking external validity, for example morphs may show ghosting artefacts by the computer graphics software (Kätsyri et al., 2019).

Several measures were taken to secure a standard of sufficient data quality in the primary study pool and therefore our meta-analysis as a summary of the quantitative results. This includes the restriction to experience of genuine technical implementations and to the Godspeed Scales as operationalizations of the key variables. We further implemented a risk of study bias assessment (Nudelman & Otto, 2020) and controlled our meta-analytic results for the respective scores. These scores revealed remarkable weaknesses regarding design or reporting. We need to acknowledge these shortcomings of the primary study data, and we emphasize two implications for human-robot interaction research:

First, our review of studies revealed that a substantial number of publications failed to report basic information on the sample and descriptive results. Authors of quantitative results sections should make sure to report (subgroup-) sample sizes and results on variance (e.g., the standard deviation) along with mean values (or any other measure of central tendency). Zero-order correlations and raw descriptive statistics are particularly helpful for (meta-analytic) summaries and comparisons within a field of research. Second, sample sizes were remarkably small, $Mdn(N) = 21$, from a general psychological perspective. They arguably reflect the studied topic in human-robot interaction research for which the technological requirements complicate or impede larger sample sizes. Nevertheless, minimal sample size recommendations should be adhered to (Simmons et al., 2011). Note that 20 participants per cell, for example, is insufficient to “detect in a representative sample that men are heavier than women” (Simmons et al., 2018, p. 256). The problem of low sample size is even more

serious for complex between-subjects designs (e.g., a focal moderation effect based on a 2 x 2 experimental design). The authors of several other recent meta-analyses and reviews in the field of human-robot interaction also identified similar problems in data reporting and statistical power of primary studies and made similar recommendations to the interdisciplinary research community (Leichtmann & Nitsch, 2020; Oliveira et al., 2021; Stower et al., 2021). We are therefore optimistic that future empirical work will benefit from the lessons learned and, through larger sample sizes and greater transparency, will make important contributions to our understanding of user responses to robots.

4.2 Conclusion

The uncanny valley hypothesis is a major perspective to explaining and predicting negative responses to humanoid and android robots. The available research covers user experiences of low to moderate human likeness, whereas robots with high human likeness are largely unchartered territory. Within these low to moderate levels of human likeness, our findings follow the assumptions derived from the uncanny valley hypothesis insofar as likability ratings initially increase but then level off to a plateau as a result of a nonlinear function. Movement appears to be no factor that intensifies the characteristic nonlinear association between human likeness and likability.

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Table 1

Descriptive Statistics for Samples Included in the Meta-Analytic Database

Variable	*Mdn / %*	*Min*	*Max*	Valid	Missing
Sample size	21	6	121	93	0%
Number of evaluations per sample	1	1	9	93	0%
Country of origin				80	14%
Germany	44%				
Italy	5%				
Japan	5%				
The Netherlands	6%				
United Kingdom	11%				
Other	29%				
Publication year	2018	2011	2020	93	0%
Percentage females	50	0	81	89	4%
Mean age	25	9	68	80	14%
Sample type				65	30%
Students / university personnel	79%				
General public	9%				
Children	3%				
Other	9%				
Publication type				93	0%
Journal article	33%				
Proceedings	55%				
Book chapter	3%				
Thesis	6%				
Other	2%				
Response scales				52	44%
5-point	89%				
6-point	4%				
7-point	8%				
Number of items for anthropomorphism				40	57%
2 items	3%				
3 items	5%				
5 items	93%				
Number of items for likability				39	58%
4 items	3%				
5 items	90%				
6 items [a]	8%				

Note. Valid = Number of samples that reported the respective information. Missing = Percentage of samples failing to report the respective information.

[a] We suspect the studies by the research group claiming to have administered a sixth item (Foster et al., 2012; Giuliani et al., 2013) to be a reporting error because Bartneck, Kulić, et al. (2009) did not present a sixth item.

Table 2

Polynomial Meta-Regression Tests for the Uncanny Valley Hypothesis

		Model 1	Model 2	Model 3	Model 4
	Intercept	8.94*** (2.10)	8.72*** (2.18)	8.66* (3.53)	6.95*** (2.07)
	Anthropomorphism				
1.	Linear term	-6.19** (2.32)	-5.57** (2.41)	-5.93+ (3.75)	-3.53 (2.31)
2.	Quadratic term	2.28** (0.85)	2.03* (0.88)	2.20 (1.30)	1.23 (0.84)
3.	Cubic term	-0.25* (0.10)	-0.22* (0.11)	-0.24 (0.15)	-0.12 (0.10)
	Control variables				
4.	Average age [a]		0.00 (0.00)		
5.	Share of women [b]		0.58* (0.26)		
	Country [c]				
6.	United Kingdom		-0.17 (0.16)		
7.	Other country		-0.23* (0.09)		
8.	Publication year [d]		0.00 (0.02)		
9.	Movement [e]		-0.14+ (0.07)	7.23 (5.37)	
10.	Communication [e]		-0.17* (0.08)		5.89 (8.80)
11.	Interaction with real robot [e]		0.02 (0.09)		
12.	Statistics reported [e]		-0.16 (0.11)		
13.	Risk of study bias [f]		-0.06 (0.04)		
	Moderating effects				
14.	1. x 8.			-10.60 (6.75)	
15.	2. x 8.			4.87+ (2.84)	
16.	3. x 8.			-0.72+ (0.40)	
17.	1. x 9.				-7.98 (9.67)
18.	2. x 9.				3.16 (3.50)
19.	3. x 9.				-0.39 (0.42)
	Random effects (τ_s / τ_e)	0.39 / 0.08	0.35 / 0.04	0.40 / 0.04	0.37 / 0.04
	I^2	96%	95%	96%	95%
	R^2	5%	23%***	3%***	17%***

Note. Dependent variable are likeability ratings. Presented are meta-regression coefficients with standard errors in parentheses. τ_s / τ_e = Standard deviations of random effects for samples and evaluations; R^2 = Explained random variance.

[a] Centered at 25 years, [b] Centered at .50, [c] Dummy coded with Germany as reference category, [d] Centered at year 2020, [e] 0 = yes, 1 = no, [f] Centered at 4.

*** $p < .001$, ** $p < .01$, * $p < .05$, + $p < .10$

Figure 1

Uncanny Valley Hypothesis (after Mori, 1970)

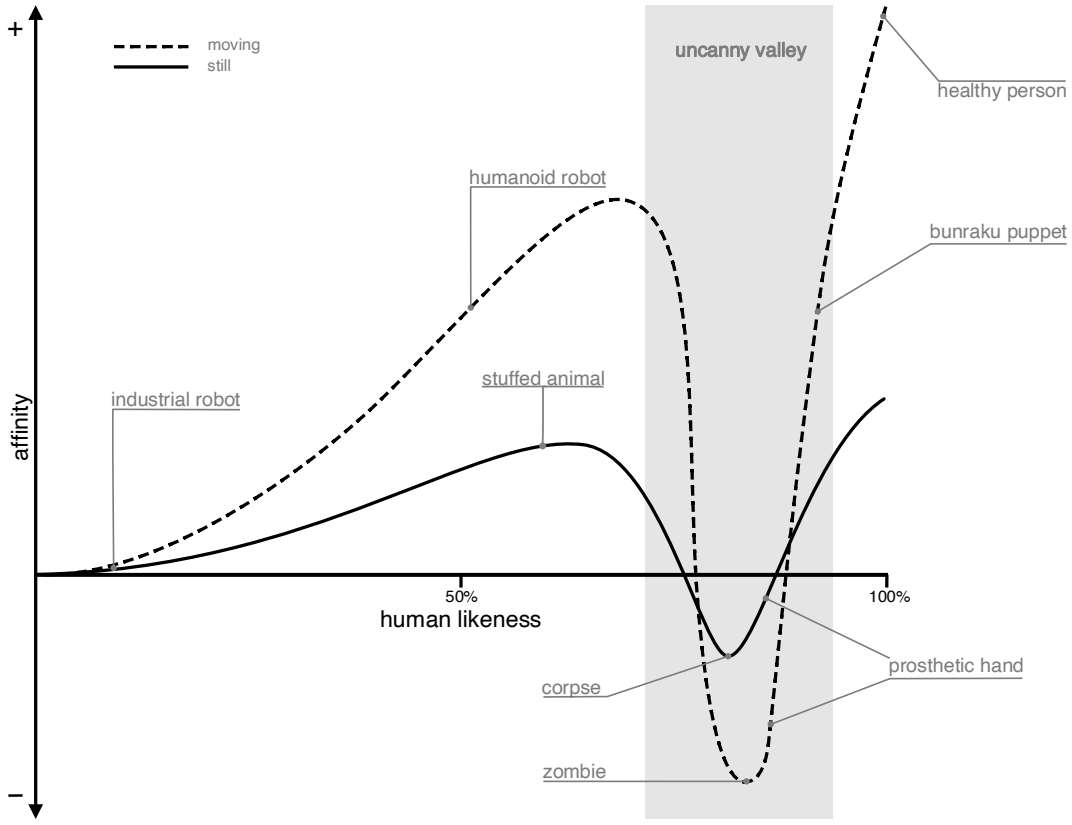


Figure 2

Average Score Distributions of the Godspeed Anthropomorphism and Likability Scales

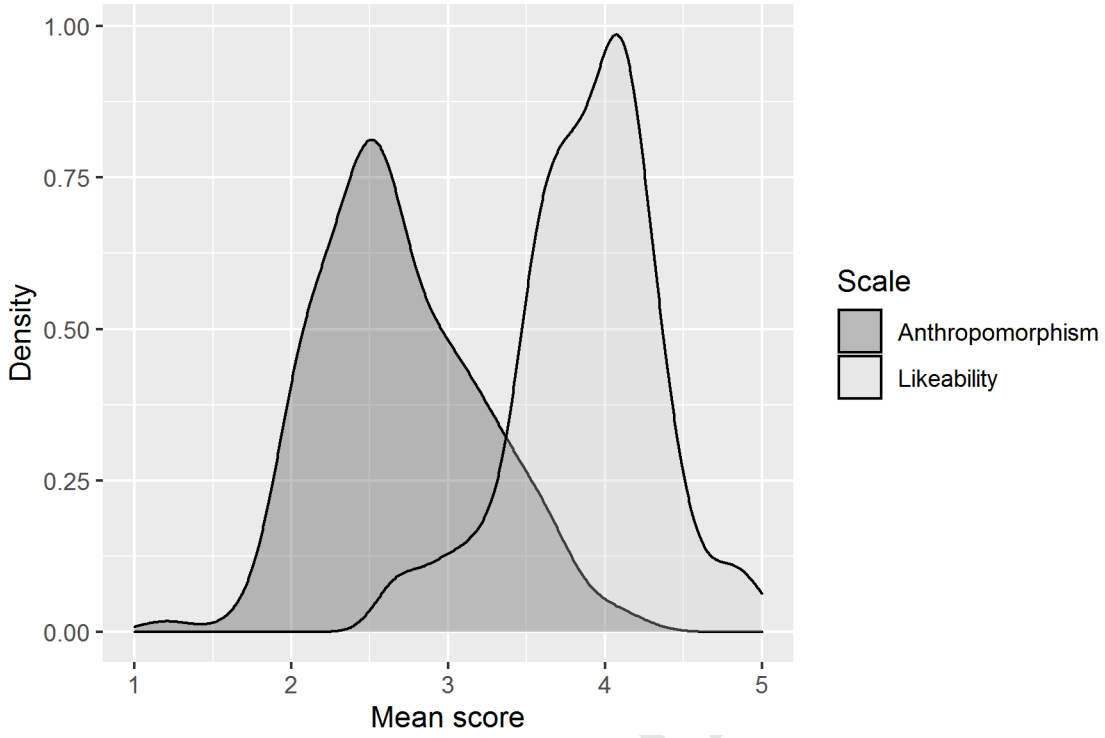
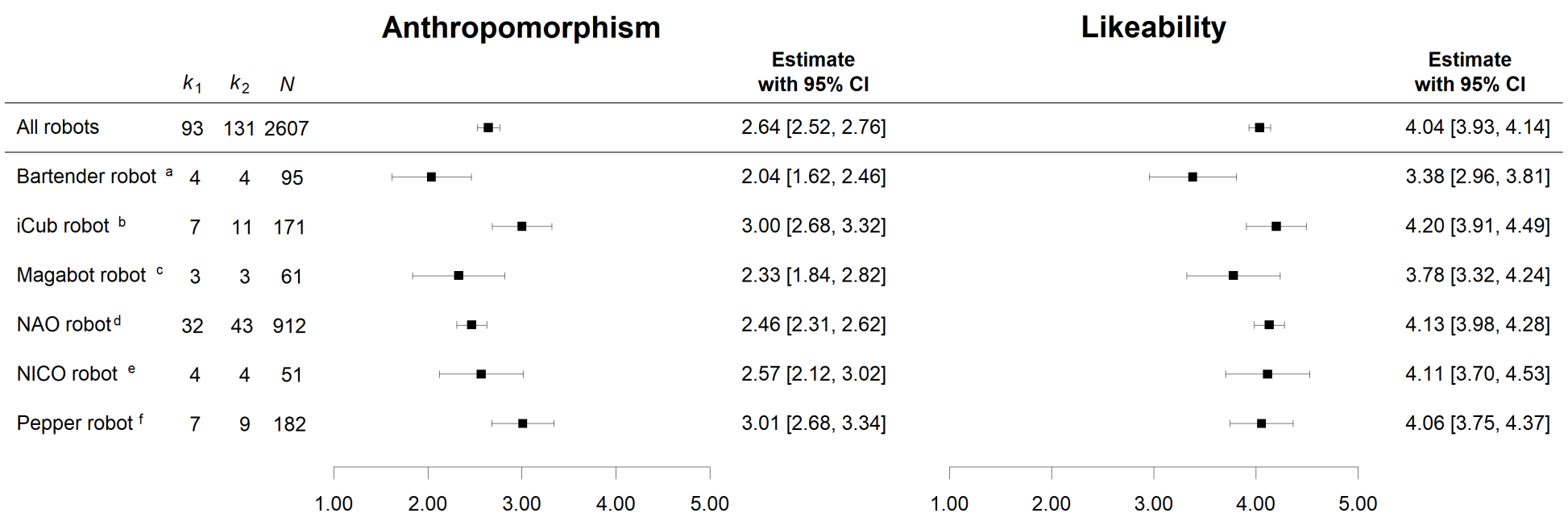


Figure 3

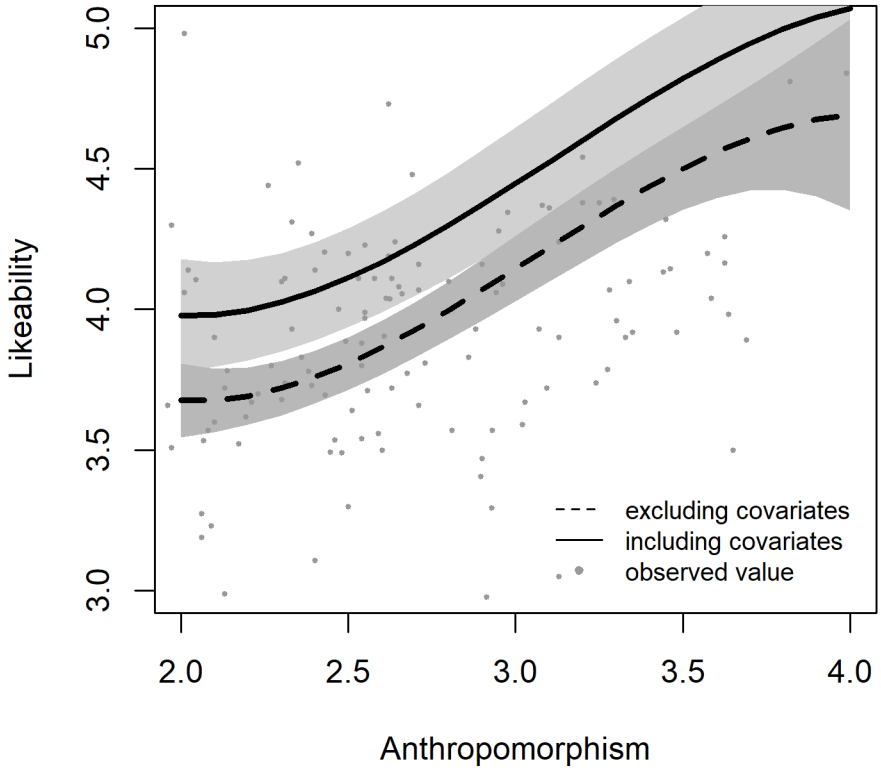
Forest Plots for Average Anthropomorphism and Likability Scores by Robot Model



Note. k_1 = Number of samples, k_2 = Number of ratings, N = Total sample size. [a] Foster et al. (2012), Giuliani et al. (2013), Keizer et al. (2014); [b] Ghiglino et al. (2020), Lehmann et al. (2016); Mazzola et al. (2020), Willemse & Wykowska (2019); [c] Hoegen (2013), Lohse et al. (2013); [d] Barlas (2019), Cuijpers et al. (2011), Ham et al. (2015), van der Hout (2017), Lehmann et al. (2020), Mirnig, Stollnberger, Giuliani, et al. (2017), Mirnig, Stollnberger, Miksch et al. (2017), Rosenberg-Kima et al. (2020), Rosenthal-von der Pütten, Bock, et al. (2017), Rosenthal-von der Pütten, Krämer, & Herrmann (2018), Schneider (2019), Zanatto, Patacchiola, Goslin, & Cangelosi (2019), Zanatto, Patacchiola, Goslin, Thill, & Cangelosi (2020); [e] Churamani et al. (2017), Kerzel et al. (2020); [f] Iwashita & Katagami (2020), Rhim et al. (2019), Straßmann et al. (2020).

Figure 4

Predicted Likability Ratings with 95% Confidence Intervals



Supplement Material for

Human-like Robots and the Uncanny Valley:

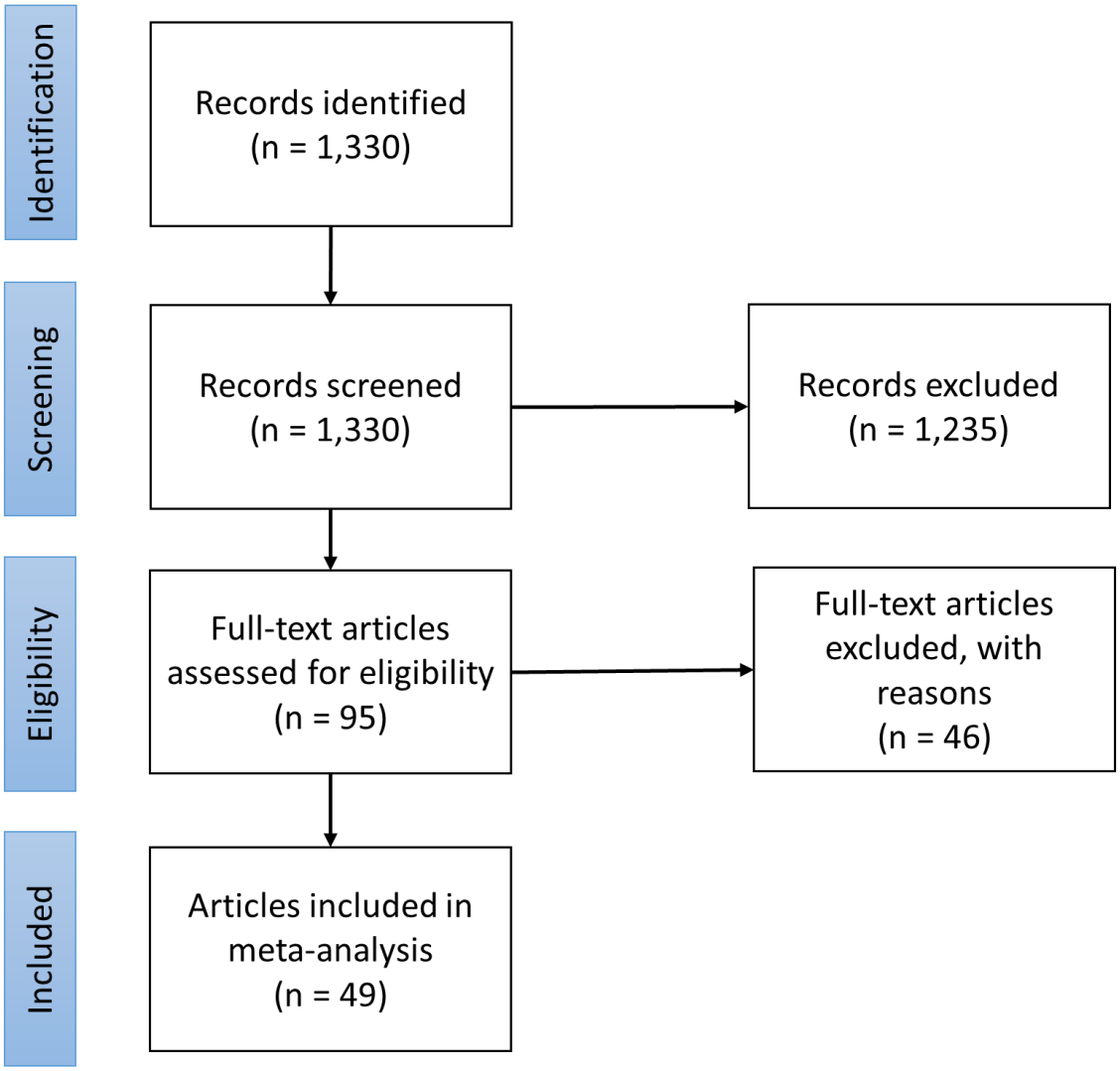
A Meta-Analysis of User Responses Based on the Godspeed Scales

Coded Variables

Variable	Description	Value	Example
study	Study ID: last name of first author + publication year	open text	schmidt2012
pubyear	Publication year	value range: [2009, 2020]	2012
sno	Unique ID for each sample	value range: [1,[	1
mno	Unique number of measure within sample	value range: [1,[	1
cntry	Country of origin of participants as ISO code	open text	DE
lang	Language of instrument	1 = English 2 = German 3 = Japanese 4 = other	1
lang2	Other language	open text	Klingon
pubtype	Publication type	1 = journal, 2 = presentation / proceedings, 3 = thesis (master/phd) 4 = book chapter 5 = other	2
robot	Description of the robot	open text	R2D2
n	Sample size	value range: [1,[	30
sample	Description of sample	open text	Undergraduates
samptype	Type of sample	0 = primarily students / university personnel 1 = general public 2 = children 3 = other	0
female	Percentage of women in sample (%)	value range: [0,100]	50
age	Mean age (in years) of participants	value range: [18,[	20
items	Number of items in anthropomorphism scale	value range: [1,[	5
m1	Mean of anthropomorphism scale	value range: [0,[	3
sd1	Standard deviation of anthropomorphism scale	value range: [0,[	1
se1	Standard error of anthropomorphism scale	value range: [0,[	1
alpha1	Cronbach's alpha for anthropomorphism scale	value range: [0,1]	0,8
items2	Number of items in likeability scale	value range: [0,[	5
m2	Mean of likeability scale	value range: [0,[	3
sd2	Standard deviation of likeability scale	value range: [0,[	1
se2	Standard error of likeability scale	value range: [0,[	1

Variable	Description	Value	Example
alpha2	Cronbach's alpha for likeability scale	value range: [0,1]	0,8
plot	Were statistics reported or derived from plots?	0 = reported 1 = from plots	0
page	Page of publication that the statistics are reported on	open text	p11
scale	Number of response scales of the administered items	value range: [2,[	5
mode	How was the robot presented?	0 = Physical presentation 1 = Photo 2 = Video 3 = other	0
mode2	How was the robot presented? other	open text	virtual environment
move	Did the robot move?	0 = not moving 1 = moving	0
talk	Did the robot talk?	0 = not talking 1 = talking	0
note	General comments	open text	

PRISMA Flow Diagram



Coded Data

Study	Year	Country	Robot	*N*	M_A	SE_A	M_L	SE_L	Real	Moving	Talking	Plot	Bias
Avelino et al. (2018)	2018	PT	Vizzy	21	3,29	0,09	4,39	0,1	yes	yes	no	yes	5
	2018	PT	Vizzy	22	2,94	0,07	4,06	0,13	yes	yes	no	yes	5
Barlas (2019)	2019	DE	NAO	30	2,62	0,11	4,04	0,01	yes	yes	yes	yes	5
	2019	DE	NAO	30	2,49	0,08	3,89	0,02	yes	yes	yes	yes	5
	2019	DE	NAO	24	2,61	0,16	4,04	0,02	yes	yes	yes	yes	5
	2019	DE	NAO	24	2,43	0,14	4,2	0,02	yes	yes	yes	yes	5
Busch et al. (2019)	2019	UK	ARMAR-6	6	2,5	0,37	3,3	0,12	no	yes	no	no	2
	2019	UK	ARMAR-6	7	2,09	0,43	3,23	0,18	no	yes	no	no	2
Churamani et al. (2017)	2017	DE	NICO	13	2,56	0,15	3,71	0,13	yes	yes	yes	yes	4
	2017	DE	NICO	14	2,58	0,09	4,11	0,09	yes	yes	yes	yes	4
Cuijpers et al. (2011)	2011	NL	NAO	14	3,44	0,21	4,13	0,22	yes	yes	no	yes	3
	2011	NL	NAO	14	3,48	0,19	3,92	0,24	yes	yes	no	yes	3
	2011	NL	NAO	14	3,63	0,17	4,16	0,22	yes	yes	no	yes	3
	2011	NL	NAO	14	3,63	0,22	4,26	0,17	yes	yes	no	yes	3
	2011	NL	NAO	14	3,46	0,2	4,14	0,22	yes	yes	no	yes	3
	2011	NL	NAO	14	3,57	0,21	4,2	0,2	yes	yes	no	yes	3
	2011	NL	NAO	14	3,33	0,17	3,9	0,2	yes	yes	no	yes	3
	2011	NL	NAO	14	3,35	0,22	3,92	0,24	yes	yes	no	yes	3
	2011	NL	NAO	14	3,58	0,19	4,04	0,24	yes	yes	no	yes	3
Foster et al. (2012)	2012		JAMES	31	2,39	0,13	3,73	0,17	yes	yes	yes	no	4
Fu et al. (2020)	2020	JP	CommU	12	2,81	0,2	3,57	0,28	yes	no	yes	no	1
	2020	JP	CommU	12	2,05	0,17	2,66	0,23	yes	no	yes	no	1
	2020	JP	CommU	12	3,28	0,21	4,07	0,15	yes	no	yes	no	1
	2020	JP	CommU	12	2,23	0,16	3,7	0,17	yes	no	yes	no	1
Ghiglino et al. (2020)	2020	IT	iCub	40	3,08	0,31	4,37	0,22	yes	yes	no	yes	3
	2020	IT	iCub	40	2,98	0,31	4,35	0,27	yes	yes	no	yes	3
	2020	IT	iCub	39	3,3	0,25	3,96	0,19	yes	yes	no	yes	3
	2020	IT	iCub	39	2,68	0,22	3,77	0,18	yes	yes	no	yes	3

Study	Year	Country	Robot	*N*	M_A	SE_A	M_L	SE_L	Real	Moving	Talking	Plot	Bias
Giuliani et al (2013)	2013		JAMES	14	1.99	0.16	2.63	0.30	yes	yes	yes	no	3
	2013		JAMES	26	1.72	0.11	3.44	0.17	yes	yes	yes	no	3
Ham et al. (2015)	2015	SG	NAO	16	2.17	0.12	3.52	0.09	yes	yes	no	yes	3
	2015	SG	NAO	16	2.44	0.14	3.49	0.16	yes	yes	no	yes	3
	2015	SG	NAO	16	2.46	0.16	3.54	0.12	yes	yes	no	yes	3
	2015	SG	NAO	16	2.30	0.16	3.68	0.23	yes	yes	no	yes	3
Haring et al. (2015)	2015	JP	Robi	20	2.54	0.13	3.8	0.19	yes	yes	no	no	2
	2015	JP	Robi	20	3.10	0.11	4.36	0.15	yes	yes	yes	no	2
	2015	JP	Robi	20	3.20	0.17	4.54	0.11	yes	yes	yes	no	2
	2015	AU	Robi	22	2.71	0.13	4.07	0.13	yes	yes	no	no	2
	2015	AU	Robi	22	2.64	0.19	4.24	0.16	yes	yes	yes	no	2
	2015	AU	Robi	22	2.96	0.22	4.09	0.25	yes	yes	yes	no	2
Haring et al. (2016)	2016	JP / AU	Geminoid-F	121	3.13	0.14	3.05	0.11	yes	yes	yes	no	4
	2016	JP / AU	Robi	64	2.31	0.10	4.11	0.11	yes	yes	yes	no	4
	2016	JP / AU	My Keepon	62	2.54	0.10	3.88	0.10	yes	no	no	no	4
Hoegen (2013)	2013	NL	Magabot	10	2.47	0.15	4.00	0.15	yes	yes	yes	no	3
	2013	NL	Magabot	11	1.97	0.19	3.51	0.14	yes	yes	yes	no	3
Iwashita & Katagami (2020)	2020	JP	Pepper	16	3.69	0.09	3.89	0.11	yes	yes	yes	yes	3
	2020	JP	Pepper	16	3.64	0.09	3.98	0.09	yes	yes	yes	yes	3
	2020	JP	Pepper	16	2.40	0.16	3.11	0.13	yes	yes	yes	yes	3
Johansson et al. (2020)	2020	NZ	EveR-4	46	2.19	0.10	3.62	0.13	yes	yes	yes	no	4
	2020	NZ	EveR-4	46	2.66	0.13	4.06	0.11	yes	yes	yes	no	4
	2020	NZ	EveR-4	45	2.14	0.10	3.78	0.12	yes	yes	yes	no	4
	2020	NZ	EveR-4	45	2.61	0.12	3.91	0.11	yes	yes	yes	no	4
Keizer et al. (2014)	2014	DE	JAMES	24	2.07	0.22	3.53	0.20	yes	yes	yes	no	4
Kerzel et al. (2020)	2020	DE	NICO	12	2.62	0.29	4.19	0.25	yes	yes	yes	no	3
	2020	DE	NICO	12	2.55	0.32	4.23	0.21	yes	yes	no	no	3
Kühnlenz (2013)	2013	DE	EDDIE	21	3.13	0.17	3.90	0.13	yes	yes	yes	no	3
	2013	DE	EDDIE	22	3.07	0.15	3.93	0.12	yes	yes	yes	no	3
	2013	DE	EDDIE	21	2.73	0.17	3.81	0.17	yes	yes	yes	no	3

Study	Year	Country	Robot	*N*	M_A	SE_A	M_L	SE_L	Real	Moving	Talking	Plot	Bias
	2013	DE	EDDIE	20	2.36	0.15	3.83	0.18	yes	yes	yes	no	3
Kühnlenz et al. (2013)	2013	DE	EDDIE	13	2.60	0.17	3.5	0.31	yes	yes	yes	no	3
	2013	DE	EDDIE	25	2.80	0.10	4.10	0.10	yes	yes	yes	no	3
	2013	DE	EDDIE	17	2.80	0.17	4.10	0.17	yes	yes	yes	no	3
Lehmann et al. (2016)	2016		iCub	14	2.63	0.06	4.11	0.05	no	no	yes	no	1
	2016		iCub	14	2.71	0.11	4.16	0.04	no	yes	yes	no	1
	2016		iCub	14	2.65	0.12	4.08	0.03	no	yes	yes	no	1
Lehmann et al. (2020)	2020	CZ	NAO	40	2.93	0.12	3.57	0.16	yes	yes	no	no	3
	2020	CZ	NAO	40	3.02	0.16	3.59	0.15	yes	yes	no	no	3
	2020	CZ	NAO	40	2.90	0.14	3.47	0.15	yes	yes	no	no	3
Löffler et al. (2019)	2019	DE	BlessU2	41	2.04	0.01	4.11	0.06	yes	yes	yes	yes	3
	2019	DE	QT	41	2.11	0.02	3.98	0.06	yes	yes	yes	yes	3
Lohse et al. (2013)	2013	NL	Magabot	40	2.54	0.11	3.54	0.09	yes	yes	no	no	3
Lugrin et al. (2018)	2018	DE	Robopec Reeti	20	2.31	0.21	3.74	0.23	yes	yes	yes	no	3
	2018	DE	Robopec Reeti	20	2.55	0.19	3.97	0.17	yes	yes	yes	no	3
Mazzola et al. (2020)	2020	IT	iCub	25	2.90	0.19	4.16	0.21	yes	yes	yes	no	5
	2020	IT	iCub	25	2.06	0.16	3.27	0.24	yes	yes	no	no	5
Meghdari et al. (2018)	2018	IR	Arash	14	4.14	0.21	4.90	0.08	yes	yes	yes	no	2
Mirnig et al. (2017a)	2017	AT	NAO	21	1.97	0.14	4.30	0.11	yes	yes	yes	no	4
	2017	AT	NAO	24	2.33	0.16	3.93	0.14	yes	yes	yes	no	4
Mirnig et al. (2017b)	2017	AT	NAO	113	2.1	0.12	3.6	0.13	no	yes	yes	no	3
Moon et al. (2013)	2013	UK	Barrett WAM robot	24	2.48	0.18	2.68	0.17	yes	yes	no	yes	4
	2013	UK	Barrett WAM robot	24	2.91	0.18	2.98	0.20	yes	yes	no	yes	4
	2013	UK	Barrett WAM robot	24	3.03	0.14	3.67	0.16	yes	yes	no	yes	4
	2013	UK	Barrett WAM robot	24	3.28	0.18	3.79	0.15	yes	yes	no	yes	4
	2013	UK	Barrett WAM robot	24	2.90	0.16	3.41	0.14	yes	yes	no	yes	4
	2013	UK	Barrett WAM robot	24	3.09	0.18	3.72	0.16	yes	yes	no	yes	4
Müller et al. (2017)	2017	DE	Virtual reality robot	76	2.06	0.08	3.19	0.07	no	yes	no	no	2
	2017	DE	Virtual reality robot	76	2.38	0.12	3.78	0.08	no	yes	no	no	2
Paetzel et al. (2020)	2020	SE	Furhead	16	3.65	0.17	3.50	0.17	yes	yes	yes	no	5

Study	Year	Country	Robot	*N*	M_A	SE_A	M_L	SE_L	Real	Moving	Talking	Plot	Bias
	2020	SE	Furhead	16	2.97	0.17	2.87	0.16	yes	yes	yes	no	5
Petrak et al. (2019)	2019	DE	Virtual reality robot	16	3.13	0.22	4.24	0.16	no	yes	no	no	3
	2019	DE	Virtual reality robot	16	2.36	0.26	2.82	0.27	no	yes	no	no	3
Rhim et al. (2019)	2019		Pepper	40	3.25	0.14	4.38	0.10	yes	yes	yes	no	3
	2019		Pepper	38	3.45	0.12	4.32	0.11	yes	yes	yes	no	3
Rosenberg-Kima et al. (2020)	2020	IS	NAO	36	2.51	0.11	3.64	0.12	yes	yes	yes	no	3
Rosenthal-von der Pütten et al. (2017)	2017	DE	NAO	20	2.01	0.22	4.06	0.17	yes	yes	yes	no	4
	2017	DE	NAO	20	2.26	0.22	4.44	0.16	yes	yes	yes	no	4
	2017	DE	NAO	20	2.01	0.17	4.98	0.18	yes	yes	yes	no	4
	2017	DE	NAO	20	2.33	0.23	4.31	0.15	yes	yes	yes	no	4
	2017	DE	NAO	20	2.4	0.19	4.14	0.15	yes	yes	yes	no	4
	2017	DE	NAO	20	2.69	0.19	4.48	0.09	yes	yes	yes	no	4
Rosenthal-von der Pütten et al. (2018)	2018	DE	NAO	20	2.10	0.20	3.90	0.20	yes	no	yes	no	4
	2018	DE	NAO	20	2.30	0.16	4.10	0.16	yes	no	yes	no	4
	2018	DE	NAO	20	2.50	0.25	4.20	0.18	yes	yes	yes	no	4
	2018	DE	NAO	20	2.50	0.22	4.20	0.13	yes	yes	yes	no	4
Ruitjen & Cuijpers (2018)	2018		Drone	64	2.13	0.13	2.99	0.13	no	no	no	no	3
	2018		Drone	64	2.48	0.14	3.49	0.14	no	yes	no	no	3
	2018		Drone	58	2.63	0.12	3.72	0.11	no	no	no	no	3
	2018		Drone	58	2.86	0.13	3.83	0.11	no	yes	no	no	3
Schneider (2019)	2019		NAO	20	2.62	0.19	4.73	0.08	yes	yes	yes	no	6
	2019		NAO	20	2.35	0.14	4.52	0.13	yes	yes	yes	no	6
Shariati et al. (2018)	2018	IR	Arash	20	3.99	0.19	4.84	0.08	yes	yes	yes	no	3
	2018	IR	Arash	20	3.82	0.18	4.81	0.07	no	yes	yes	no	3
Straßmann et al. (2020)	2020	DE	Pepper	22	2.27	0.19	3.80	0.16	yes	no	yes	no	4
	2020	DE	Pepper	22	2.53	0.12	4.11	0.14	yes	no	yes	no	4
	2020	DE	Pepper	22	2.13	0.14	3.72	0.14	no	no	yes	no	4
	2020	DE	Pepper	22	1.96	0.13	3.66	0.13	no	no	yes	no	4
Syrdal et al. (2013)	2013	UK	Sunflower housing robot	8	3.20	0.38	4.38	0.06	yes	yes	no	no	2
	2013	UK	Sunflower housing robot	8	2.88	0.35	3.93	0.07	yes	no	no	no	2

Study	Year	Country	Robot	*N*	M_A	SE_A	M_L	SE_L	Real	Moving	Talking	Plot	Bias
Trovato et al. (2015a)	2015	BR	KOBIAN	40	2.59	0.15	3.56	0.12	no	no	yes	no	6
Trovato et al. (2015b)	2015	BR	KOBIAN	20	1.20	0.20	4.65	0.22	no	no	yes	no	6
Ueno et al. (2020)	2020	CZ	Robot hand	23	2.93	0.19	3.30	0.17	yes	no	no	yes	3
Van der Hout (2017)	2017	NL	NAO	67	2.21	0.11	3.67	0.10	yes	yes	yes	no	4
	2017	NL	NAO	67	2.43	0.11	3.70	0.11	yes	yes	yes	no	4
Wieser et al. (2016)	2016		IRMA	20	2.95	0.15	4.28	0.13	yes	yes	no	no	4
Willemse & Wykowska (2019)	2019	IT	iCub	25	3.34	0.14	4.10	0.14	yes	yes	yes	no	4
	2019	IT	iCub	25	3.24	0.16	3.74	0.15	yes	yes	yes	no	4
Zanatto et al. (2019)	2019	UK	NAO	48	2.39	0.11	4.27	0.15	yes	yes	yes	no	5
	2019	UK	NAO	48	2.55	0.13	3.99	0.12	yes	no	no	no	5
Zanatto et al. (2020)	2020	UK	NAO	30	2.08	0.10	3.57	0.07	yes	yes	no	no	3
	2020	UK	NAO	29	2.71	0.10	3.66	0.11	yes	yes	no	no	3
	2020	UK	NAO	30	2.02	0.10	4.14	0.08	yes	yes	no	no	3

Note. $M_{A/L}$ = Mean anthropomorphism (A) or likability (L) score. $SE_{A/L}$ = Standard error for $M_{A/L}$. Real = Participants interacted with a real robot as compared to a photo or video. Plot = Statistics were reproduced from plots. Bias = Risk of bias using the ROBUST (Nudelman & Otto, 2020) codings.

Reliability Generalizations

The coefficient alpha reliabilities were pooled across samples with a random-effects meta-analysis using restricted maximum likelihood estimation. Because raw coefficient alphas are not normally distributed, we used the transformation and large sample variances suggested by Hakistan and Whalen (1976). To account for different test lengths (i.e., samples administering short versions), the coefficient alphas were corrected to a length of 5 items (i.e., as in the original scales) using the Spearman-Brown prophecy formula. Moreover, the average score variances were included as moderators in the meta-analytic models to adjust for range restriction (cf. Rodriguez & Maeda, 2006). The results of the two reliability generalizations in Table S1 show that both scales were generally reliable with pooled coefficient alphas of .85 und .88 for anthropomorphism and likability, respectively. For anthropomorphism, there was little variation between samples as indicated by the non-significant random component and the small value of I^2. Although the respective effect was slightly larger for likability (I^2 = 34%), unaccounted differences between samples can be considered moderate. Overall, these analyses highlight that, on average, both Godspeed scales exhibited satisfactory reliabilities in the studied samples.

Table S1

Reliability Generalizations of the Godspeed Anthropomorphism and Likability Scales

	Anthropomorphism	Likability
Number of samples	34	34
Pooled coefficient alpha	.850	.883
95% Confidence interval	[.830, .869]	[.867, .899]
95% Credibility interval	[.796, .894]	[.819, .930]
I^2	17.23%	34.03%
Test of residual heterogeneity	$Q(df = 32) = 35.817$, $p = .294$	$Q(df = 27) = 45.019$, $p = .063$
Test of moderator effects	$Q_m(df = 1) = 3.125$, $p = .077$	$Q_m(df = 1) = 0.328$, $p = .567$

Meta-Analyses of Godspeed Scale Scores by Robot

Differences in anthropomorphism and likability ratings between different robot models were examined by meta-analytically pooling the coded mean scores and using the robot model as a predictor in a meta-regression. We distinguished six robots for which ratings from at least three independent samples were available: the bartender robot JAMES (e.g., Foster et al., 2012; Giuliani et al., 2013), the iCub robot by the Italian Institute of Technology (e.g., Mazzola et al., 2020), the Magabot robot (e.g., Lohse et al., 2013), the NAO robot by SoftBank Robotics (e.g., Cuijpers et al., 2011), the neuro-inspired companion robot NICO by the Knowledge Technology group at the University of Hamburg (e.g., Kerzel et al., 2020), and the Pepper robot by SoftBank Robotics (e.g., Iwashita and Katagami, 2020). To correct for potential setting effects, the presentation mode (real versus other) and whether the robot moved or communicated were included as covariates. The covariates were dummy coded, while the robot model was effect-coded to determine the difference of a specific model from the overall mean rating. For each scale, results of two meta-analytic models are presented (see Table S2): (a) a model that included only the covariates (Model 1) and (b) a model that additionally accounted for differences between the six robot models (Model 2).

The pooled anthropomorphism score across all robot models was $\mu = 2.64$, 95% CI [2.52, 2.76]. In line with Mori's hypothesis (Mori et al., 2012), moving robots were evaluated more human-like as compared to static robots. Moreover, robots seemed to be attributed more human-like characteristics when respondents interacted with a real robot as compared to simply viewing photos or videos of a robot. However, these effects were only significant after accounting for differences between robot types (Model 2). We also observed significant differences in anthropomorphism ratings between robot models. While the bartender robot JAMES was evaluated significantly less human-like as compared to the average evaluation, the iCub robot and Pepper were evaluated significantly more human-like (see Table S2). The

robot model accounted for about 20% in the random variance of anthropomorphism ratings between samples.

The pooled likability score across all robot models was μ = 4.04, 95% CI [3.93, 4.14]. Robots that communicated with the respondents (e.g., talked) were evaluated significantly ($p < .05$) more likeable as compared to mute robots. Again, we also observed significant differences in likability ratings between robot models. While the bartender robot JAMES was evaluated significantly less likeable as compared to the average evaluation, the NAO robot was evaluated significantly more likeable (see Table S2). The robot model explained about 4% in the random variance of likability ratings between samples.

Table S2

Meta-Analyses of Godspeed Scale Scores by Robot Model

	Anthropomorphism		*Likability*	
	Model 1	Model 2	Model 1	Model 2
Intercept	2.64*** (0.06)	2.61*** (0.07)	4.04*** (0.05)	3.95*** (0.07)
Bartender robot [c]		-0.57** (0.20)		-0.57** (0.20)
iCub robot [c]		0.39** (0.15)		0.25+ (0.14)
Magabot robot [c]		-0.28 (0.22)		-0.18 (0.21)
NAO robot [c]		-0.14 (0.09)		0.17* (0.09)
NICO robot [c]		-0.04 (0.20)		0.16 (0.19)
Pepper robot [c]		0.40* (0.16)		0.10 (0.15)
Presentation mode [a]	-0.17 (0.13)	-0.36** (0.13)	-0.10 (0.11)	-0.12 (0.11)
Moving [b]	-0.22+ (0.12)	-0.32** (0.12)	-0.15 (0.11)	-0.16 (0.11)
Communicating [b]	0.03 (0.10)	0.03 (0.03)	-0.26** (0.08)	-0.29*** (0.08)
Random effect (τ^2)	0.36 / 0.27	0.31 / 0.25	0.30 / 0.25	0.29 / 0.25
I^2	95%	93%	96%	95%
R^2	3%	23%	9%	13%

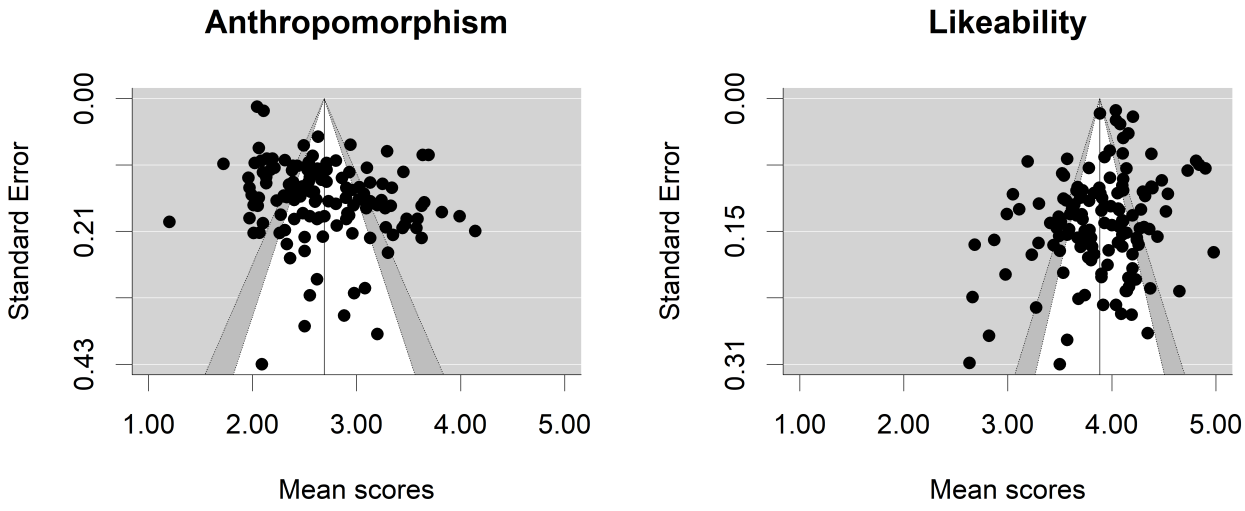
Note. Presented are meta-regression coefficients with standard errors in parentheses.
[a] 0 = physical, 1 = other ; [b] 0 = yes, 1 = no; [c] Effect-coded with other robots as reference category.
*** $p < .001$, ** $p < .01$, * $p < .05$, + $p < .10$

Analysis of Publication Bias

The presence and consequence of a potential publication bias were examined separately for the two Godspeed scales. The funnel plots in Figure S1 indicated a slightly asymmetric shape for the likability scores. However, this might be a consequence of a ceiling effect because many scores clustered in the upper region at the border of the scale limit. For anthropomorphism scores, a visual inspection of the funnel plot did not indicate a pronounced asymmetry.

Figure S1

Funnel Plots for Average Anthropomorphism and Likability Scores



The shapes of the funnel plots were tested for asymmetry using a regression test (Egger, Smith, Schneider, & Minder, 1997; Stanley, 2008) that predicted the mean scores from their standard errors. A significant effect would indicate an asymmetric shape of the funnel plot and potentially selective reporting. For anthropomorphism, the regression test suggested a skewed funnel plot (see Table S3). The pooled effect corrected for selective reporting ($\mu = 2.10$) was slightly smaller than the uncorrected effect ($\mu = 2.36$), indicating that some studies with low anthropomorphism ratings might be missing from the meta-analytic

database. In contrast for likability, the test for funnel plot asymmetry was not significant (p = .058). Moreover, the corrected (μ = 4.06) and uncorrected effect (μ = 4.01) were rather similar which does not suggest pronounced reporting bias. Taken together, these analyses suggest that publication bias might have slightly distorted the publicly available research findings regarding anthropomorphism but did not give evidence of distortions for likability ratings.

Table S3

Regression Tests for Funnel Plot Asymmetry of the Godspeed Scale Scores

	Anthropomorphism		*Likability*	
	Model 1	Model 2	Model 1	Model 2
Intercept	2.36*** (0.04)	2.10*** (0.06)	4.01*** (0.03)	4.06*** (0.04)
Standard error		3.22*** (0.55)		-1.04+ (0.54)

*** $p < .001$, ** $p < .01$, * $p < .05$, + $p < .10$

Identification of Nonlinearity

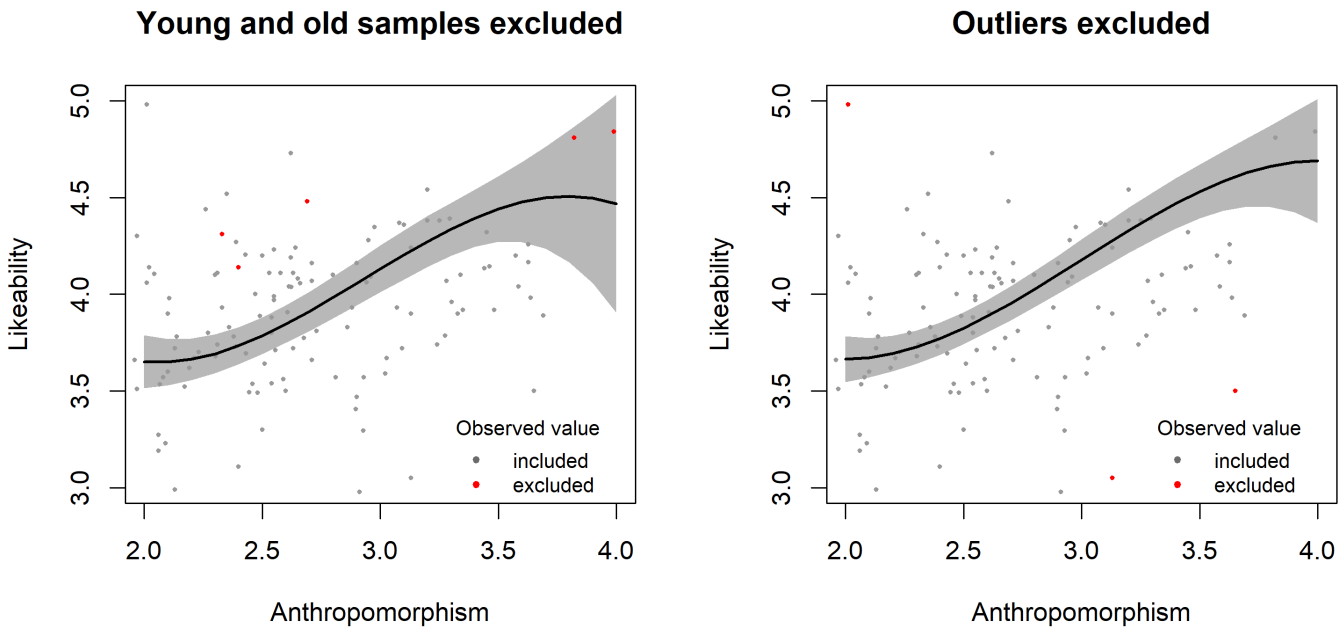
The optimal number of higher-order polynomials predicting likability from anthropomorphism was identified by comparing increasingly complex models. Models including polynomials of degree 1 to degree 6 resulted in Bayesian information criteria (BIC; Schwarz, 1978) of 130, 130, 129, 133, 138, and 142, respectively. The lowest BIC was observed for a model including polynomials of degree 3. The results of respective meta-regression analyses are summarized in Table 2.

Sensitivity Analyses

Following Voracek and colleagues (2019), we tried to determine the generalizability of the results with regard to various methodological choices. First, we repeated the meta-analyses excluding samples with children (Meghdari et al., 2018; Shariati et al., 2018) or older respondents (Rosenthal-von der Pütten et al., 2017). Because most studies relied on student samples that were rather homogenous regarding mean age, children and seniors might distort the effect estimates. However, the predicted effect with and without these samples was highly similar and replicated the curvilinear association between anthropomorphism and likability (see left panel in Figure S2). Then, we identified outliers using studentized residuals (cf. Viechtbauer & Cheung, 2010) and repeated the analyses excluding the three identified extreme values (Haring et al., 2016; Paetzel et al., 2020; Rosenthal-von der Pütten et al., 2017). Again, the resulted predicted effects between anthropomorphism and likability closely replicated the overall analyses (see right panel in Figure S2).

Figure S2

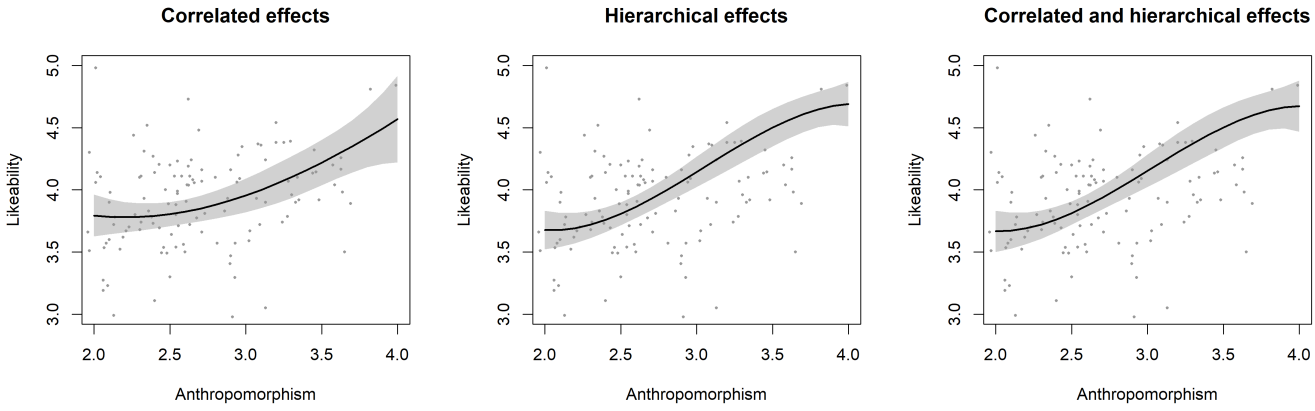
Predicted Effects Excluding Young and Old Samples or Outliers



Finally, we estimated meta-analytic models with cluster-robust standard errors (cf. Hedges et al., 2010). This involves two steps: First, preliminary standard errors are estimated using a working model that specifies a hypothesized dependency structure between observed effects. Then, the estimated standard errors are corrected for remaining unmodeled (unknown) dependencies using a sandwich estimator. Following Pustejovsky and Tipton (2021), we adopted three different working models that either assumed correlated effects, a hierarchical effect structure, or both. The predicted associations between likability and anthropomorphism for these analyses estimated with the *clubSandwich* package version 0.5.3 (Pustejovsky, 2021) are presented in Figure S3. Generally, the different modeling strategies lead to similar results; albeit ignoring a hierarchical effect structure seemed to exhibit a somewhat flatter increase. Thus, the choice of the analysis model does not substantially impact the observed results.

Figure S3

Predicted Effects Using Robust Meta-Analyses with Different Working Models



PRISMA 2020 Checklist

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Page 3
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Page 2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Page 6
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Page 7
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Page 8
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Page 7
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Page 7
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	-
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Page 9
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Supplement
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Supplement
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Page 9
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	Page 9
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	-
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	-
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	-
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the	Page 9

Section and Topic	Item #	Checklist item	Location where item is reported
		model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Page 10
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Page 10
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Supplement
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Page 10
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Page 11
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	-
Study characteristics	17	Cite each included study and present its characteristics.	Supplement
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Supplement
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Supplement
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Supplement
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Page 12-14 Supplement
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Supplement
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Supplement
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Supplement
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Supplement
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Page 14/15
	23b	Discuss any limitations of the evidence included in the review.	Page 16/17
	23c	Discuss any limitations of the review processes used.	Page 16/17
	23d	Discuss implications of the results for practice, policy, and future research.	Page 17
OTHER INFORMATION			

Section and Topic	Item #	Checklist item	Location where item is reported
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Page 1
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Page 1
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	-
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	-
Competing interests	26	Declare any competing interests of review authors.	Page 1
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Page 1/10

From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71
For more information, visit: http://www.prisma-statement.org/

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