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The Phenotypes of Anthropomorphism and the Link to Personality Traits

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Abstract

Facing robotic agents, we cannot help but ascribe them anthropomorphic characteristics. While this cognitive process has been extensively studied, numerous questions remain about how the tendency to anthropomorphize is related to individual differences and personality traits (i.e. phenotypes). Understanding what generates inter-individual differences is crucial since these differences can explain an important part of the representations and therefore behaviors towards robots. In two studies we aimed to evaluate the idea that anthropomorphism and appraisal of robots can be related to individual phenotypes. We also investigated the relationship between personality traits and anthropomorphic phenotypes. Our results support the idea that anthropomorphism can be considered a phenotype with clear individual differences in anthropomorphic tendencies based on a 2×2 anthropomorphism tendency/appraisal matrix.

Keywords Anthropomorphism · Personality · Attributions · Human-Robot Interaction

1 Introduction

Anthropomorphism is the process of attributing human physical and/or mental characteristics to various non-human entities. According to Epley and colleagues [1], anthropomorphism (conceptualized as a stable trait) is the result of "cultural embedding" defined as norms one adopts from one's environment, experience, education, or cognitive reasoning styles. In the present paper, we adopt this view of anthropomorphism and we combine it with Fisher's distinction between imaginative and an interpretative anthropomorphism [2]. The former is an a priori representation of non-human entities with human-like characteristics, whereas the latter is an interpretation of an entity's behavior or appearance through a human-biased lens (e.g., seeing the front of a car as a "face" or interpreting behaviour of geometrical figures as intentional). In sum, according to Fisher, anthropomorphism can be partly discussed as resulting from a trait. In psychology, traits contribute causally to the development of habits, attitudes, skills, and other characteristic adaptations and are a constitutive element of the personality of an individual [3]. According to McCrae and colleagues an individual's characteristic adaptation predicts proximally how one engages in an interaction with the environment whereas the underlying personality traits distally predict how one engages in an interaction with the environment [3]. Therefore, we could formulate the hypothesis that more than a process, anthropomorphism could be similar to underlying personality traits constitutive of the phenotype of personalities. As such, we could identify "groups" of (trait) anthropomorphizers. Because personality traits have been shown to be useful in predicting cognitions, emotions, and behaviors in many situations, they may be essential for understanding interpersonal differences in anthropomorphism and how individuals may differ in their relationship with robots.

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Understanding how anthropomorphism is structured differently between individuals also allows us to understand how a robot must adapt to these individualities.

Based on Epley and colleagues' framework [1], we propose that the imaginative form of anthropomorphism could be considered as an individual tendency, as a phenotype, related, at least in part, to individuals' personality traits. A recent study showed that individuals could indeed be clustered according to their "tendency to anthropomorphize" based on the evaluation of various robots' pictures [4]. The authors showed that while the design of the robot may have an impact on anthropomorphic (interpretative) attributions, the imaginative anthropomorphism (a priori representation) was the main predictor of participants' anthropomorphic attributions, with the robot design being only a moderator. Therefore, characterizing the tendency to anthropomorphize as a phenotype feature could make it possible to delineate a new framework of anthropomorphism patterns. Based on these results, one could consider distinguishing two categories of individuals: high vs. low tendency to anthropomorphize.

However, while informative, this approach remains mono-dimensional, which could be misleading with respect to delineation of actual phenotypes. Anthropomorphism is a neutral phenomenon (i.e., we cannot value anthropomorphism with positive or negative appraisal) but pertains to automatic social evaluation processes that may result in representations of robots associated to a positive or negative appraisal depending on the observer [5]. Indeed, while some research demonstrated the positive role of anthropomorphism in robot acceptance [6, 7] other studies showed that the attribution of higher degree of human-like (physical or mental) characteristics may impair acceptance [8, 9]. A large body of literature has demonstrated that expectations, attitudes, prior representations, beliefs, etc. affect how one will consider robots [10, 11]. Acknowledging results of this research, we consider the evaluation of robots in terms of (positive/negative) appraisal as a dimension complementary to anthropomorphism. As a result, we propose to delineate a 2×2 matrix of anthropomorphism: low/high anthropomorphism x negative/positive appraisal.

Defining anthropomorphism as a trait, another important factor is that it refers to the concept of personality traits as a combination of a person's emotional characteristics, attitudes, and behaviors. We propose that clustering individuals' anthropomorphic attributions might result in clusters that differ also on the personality traits. For instance, Epley and colleagues theorized that people with a higher tendency to anthropomorphize would also be those who most likely value control over their environment [1] which was later confirmed in [4, 12]. In Kaplan and colleagues' study, participants were required to complete a personality evaluation questionnaire and subsequently rate a robot on anthropomorphic characteristics. The results showed that the more extroverted, the higher anthropomorphic attributions [7]. These results were in line with those found by De Graaf and colleagues [13].

Grounding our work in Kaplan and colleagues' methodology [7], we designed the first experiment with the aim to examine the main personality traits (i.e., the extended "Big Five" framework [14]) that may differ in our 2×2 hypothesized matrix and how these differences could modulate the differences in anthropomorphic attributions between individuals. In the second experiment, building on results of Experiment 1, we focused on two traits that proved to have higher impact on anthropomorphism (i.e., the need for cognition, and the need for closure).

2 Experiment 1

As we conceptualize the tendency to anthropomorphize as an individual phenotype, we have to consider the interplay between this trait and the fundamental personality traits along the Big Five framework [15]. In psychology, the "Big Five" is a descriptive model of personality in five central traits used as a reference point for the description of personality: (1) Extraversion, as a measure of intensity of interaction with the outside world; (2) Agreeableness, reflected in the desire for cooperation and social harmony; (3) Conscientiousness, describing how the individual controls, regulates and directs his or her impulses; (4) Neuroticism which refers to a disposition to negative emotions and lack of emotional stability; and finally, (5) Openness to Experience, related to open-mindedness and curiosity. However, the literature has demonstrated that these five categories could be further divided in aspects, such as: (1) volatility and withdrawal for neuroticism dimension, (2) compassion or politeness for the agreeableness dimension, (3) industriousness or orderliness for the conscientiousness dimension, (4) enthusiasm or assertiveness for the extraversion dimension, and (5) intellect or imagination for the openness to experience dimension [16].

Although personality traits are the fundamental factors influencing how an individual interacts with the environment [15], little research has been done to link personality traits with attitudes towards robots, or with the likelihood of attributing human-like characteristics to robots [7]. The present experiment aimed to test (1) the 2×2 anthropomorphism matrix hypothesis (low/high anthropomorphism x negative/positive appraisal), and (2) the phenotype differences in terms of personality traits that could explain, at least in part, the differences in anthropomorphic attributions.

Table 1 First cluster solution. Centroids in function of cluster and factors. Factors are presented by order of importance for the clustering solution from left to right

		Agency		Sociability		Animacy		Disturbance		N
		μ	σ	μ	σ	μ	σ	μ	σ	
Cluster	1	3.38	1.26	5.20	1.21	3.24	1.56	2.66	1.19	45
	2	5.28	0.76	5.31	0.90	3.05	1.22	2.99	1.08	31
	3	5.45	0.75	5.65	0.62	5.24	1.02	5.22	1.08	19
	Combined	4.41	1.42	5.33	1.02	3.58	1.59	3.28	1.49	95

2.1 Method Experiment 1

Participants were 48 males and 47 females (Mage = 35.75, SD = 10.58) recruited online on Prolific. Sample size was determined on the basis of the desired power (0.90), alpha level (0.05), and anticipated f^2 effect size 0.05 (small effect size) in linear multiple regression models with 14 variables (described at continuation). Using G*Power 3.1 [17], the minimum required sample size was calculated as 88.

Participants first had to complete the Big Five Aspects Scales [16] that measures 2 additional dimensions for each of the 5 personality traits described earlier (see Big-Five model; Goldberg, 1992). Each personality trait was assessed by 4 to 6 positive items (e.g., "Sympathize with others' feelings.", "Have a vivid imagination."). Participants evaluated to what extent each description described them from 1 "not at all" to 7 "totally".

Second, participants filled out The Human-Robot Interaction Evaluation Scale (HRIES) [18] that involves four subdimensions (16 items) including Sociability (e.g., Warm), Agency (e.g., Self-reliant), Animacy (e.g., Alive), and Disturbance (e.g., Creepy). We operationalized appraisal (from the 2 × 2 matrix) as the disturbance subscale of the HRIES. This scale makes it possible to evaluate static, in-motion, or interactive robots on a broad spectrum of anthropomorphic attributions and provides a reliable psychometric assessment of anthropomorphic tendency. Again, for each item participants rated whether they agreed or disagreed (scale from 1 to 7) with attributing respective characteristics to an iCub robot selected because of its average human-likeness [19]. The iCub robot was simply presented as a social robot.

2.2 Results

Data are available at https://osf.io/j2buh/.

Anthropomorphic phenotypes. To evaluate the reliability of phenotypes in anthropomorphism, we conducted a two-step clustering [20] using Disturbance, Agency, Sociability, and Animacy measures (min-max normalized) to classify participants according to anthropomorphic patterns [21]. The clustering aims to divide a set of data into different homogeneous groups based on common characteristics (computational similarity) compared to the dissimilarities of the other groups. The clustering developed a 3-cluster matrix (see Table 1) with a 2.37 ratio size and a cluster quality = 0.5. These indices helped to measure the cohesion and separation of clusters. The present indices represent a good fit.

According to a cluster silhouette and cluster comparisons, results argue for a low vs. high anthropomorphism tendency, with a modulating role of appraisal on the cluster solution (disturbance dimension). We found significant differences between clusters on agency, $F(2,95) = 42.49$, $p < .001$, $\eta^2_p = .49$; animacy, $F(2,95) = 13.45$, $p < .001$, $\eta^2_p = .23$; and disturbance dimensions, $F(2,95) = 30.47$, $p < .001$, $\eta^2_p = .41$, but not on the sociability dimension, $F(2,95) = 1.17$, $p = .314$, $\eta^2_p = .03$,. Contrasts with Bonferroni correction showed that clusters 1 and 2 only differed significantly on the agency attributions, $F(1,75) = 48.77$, $p < .001$, $\eta^2_p = .41$. Whereas, clusters 2 and 3 differed significantly on both the animacy, $F(1,49) = 23.54$, $p < .001$, $\eta^2_p = .34$, and the disturbance attribution, $F(1,49) = 31.04$, $p < .001$, $\eta^2_p = .41$. Finally, cluster 1 and 3 differed on the animacy, $F(1,63) = 21.44$, $p < .001$, $\eta^2_p = .27$, agency, $F(1,63) = 37.09$, $p < .001$, $\eta^2_p = .39$, and disturbing attribution, $F(1,63) = 54.05$, $p < .001$, $\eta^2_p = .48$. In summary, the results show that it is possible to identify a cluster for "low anthropomorphizers" (cluster 1), two clusters of "high anthropomorphizers" including one group of individuals that do not attribute animacy traits to a robot (cluster 2) one group which attribute animacy traits to robots (cluster 3) but appraise them more negatively compared to the two other groups (Fig. 1). Therefore, the hypothesis on the orthogonal tendency/appraisal matrix was not confirmed.

Interaction between anthropomorphic phenotypes and personality traits. We further compared the anthropomorphic clusters with the personality traits to investigate the overlap between the two, and whether the differences of personality traits between anthropomorphic clusters could explain, at least in part, the attributions of agency, sociability, animacy or disturbing trait attributions. We used a mediation model analysis (with age, gender and level of education as covariates) including the anthropomorphic clusters as IVs, the personality traits as mediators and the attributions as DVs using Process in SPSS. This approach made it possible to compare the clusters on the personality trait dimension but also to test how these differences modulate the anthropomorphic attributions with a low vs. high

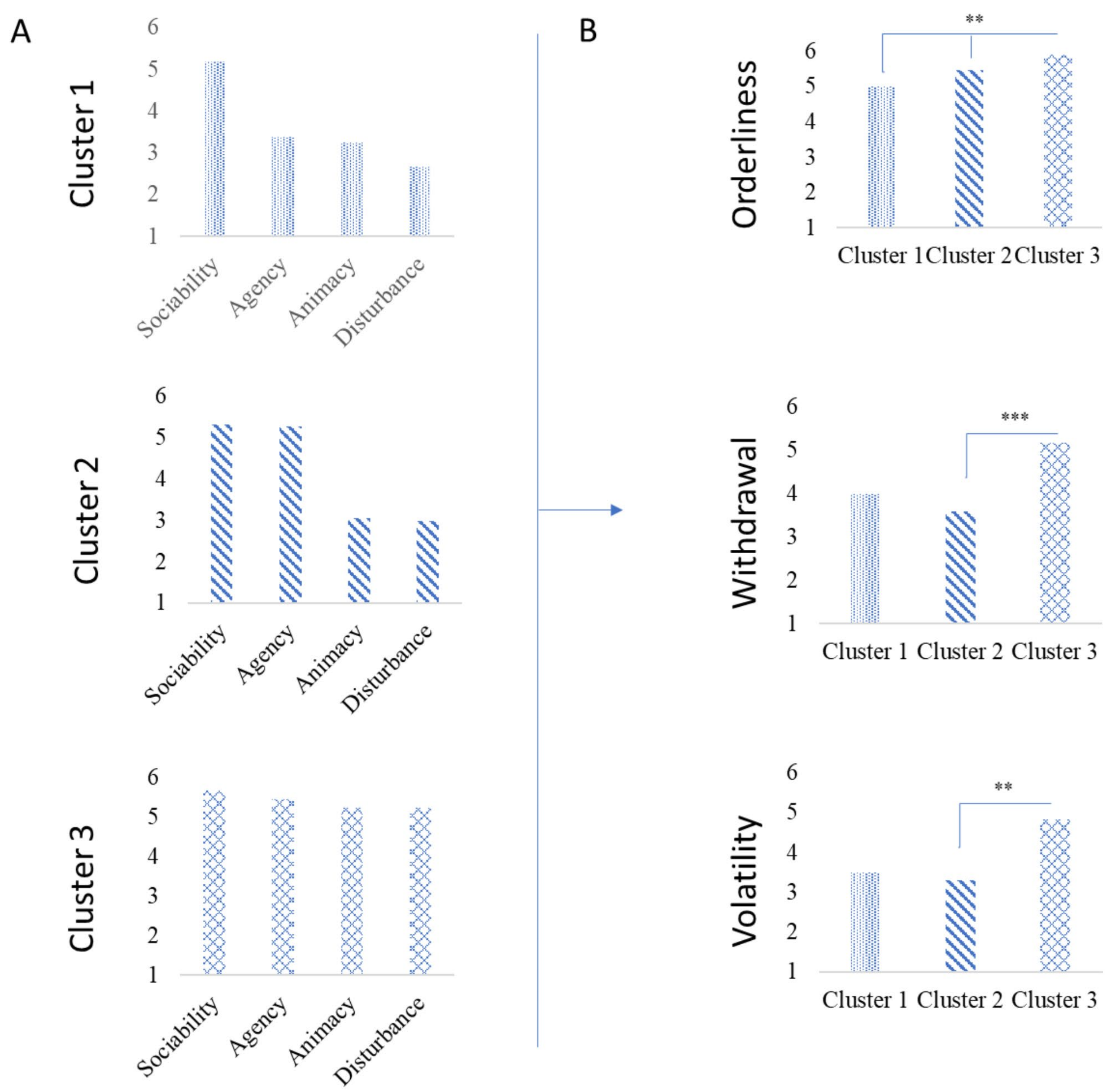

Fig. 1 Comparison between anthropomorphic phenotypes (clusters, panel A) and personality traits (panel B)

anthropomorphism contrast and a low vs. high animacy/disturbance contrast: cluster 1 (i.e., low anthropomorphizers), cluster 2 (i.e., high anthropomorphizers, positive appraisal), cluster 3 (i.e., high anthropomorphizers, negative appraisal) [-1.0, 0.5, 0.5; 0, -0.5, 0.5].

Volatility (neuroticism). Results showed first that anthropomorphic clusters differed on volatility (e.g., "Get upset easily"), $F(2,94) = 5.45$, $p = .006$, $\eta^2_p = .11$. Mediation contrasts showed a significant difference between cluster 2 and 3, $b = 0.96$, $t(92) = 3.16$, $p = .002$, $CI_{95\%}[0.36; 1.57]$, with a significant mediation on animacy, $b = 0.33$, $SE^{boot} = 0.18$, $CI_{95\%}^{boot}[0.04; 0.75]$. Also, the higher the volatility traits, the higher the animacy attributions in cluster 3 compared to cluster 2.

Withdrawal (neuroticism). Results were also significant on withdrawal trait (e.g., "Am filled with doubts about things"), $F(2,94) = 5.96$, $p = .004$, $\eta^2_p = .12$. Contrasts showed that cluster 3 was significantly higher than cluster 2 on withdrawal, $b = 1.07$, $t(92) = 3.48$, $p < .001$, $CI_{95\%}[0.46; 1.67]$, but no mediation to anthropomorphic attributions.

Orderliness (conscientiousness). Clusters also differed on orderliness (e.g., "Want every detail taken care of"),

$F(2,94)=5.87$, $p=.004$, $\eta^2_p=.12$. Contrasts showed a significant difference on contrast 1 (cluster 1 was lower than 2/3), $b=0.63$, $t(92)=3.21$, $p=.002$, $CI_{95\%}[0.24; 1.02]$, and a tendency on the contrast 2 (cluster 2 tended to be lower than cluster 3) $b=0.52$, $t(94)=1.75$, $p=.083$, $CI_{95\%}[-0.07; 1.11]$. We mention this non-significant direct effect because of the significant mediation. Indeed for both contrasts 1, $b=-0.26$, $SE^{boot}=0.12$, $CI_{95\%}{}^{boot}[-0.53; -0.08]$, and 2, $b=-0.21$, $SE^{boot}=0.14$, $CI_{95\%}{}^{boot}[-0.54; -0.01]$, the mediation was significant for disturbance attribution. The higher the orderliness, the lower the difference between anthropomorphic clusters 1 and 2/3, also between clusters 2 and 3 on disturbance attribution. Also the higher the orderliness, the higher the difference between clusters 1 and 2/3, $b=0.21$, $SE^{boot}=0.10$, $CI_{95\%}{}^{boot}$ [0.05; 0.45], and clusters 2 and 3, b = 0.18, $SE^{boot}=0.12$, $CI_{95\%}{}^{boot}[0.01; 0.44]$, on agency attribution, and animacy, $b=0.27$, $SE^{boot}=0.13$, $CI_{95\%}{}^{boot}$ [0.06; 0.58], b = 0.23, $SE^{boot}=0.14$, $CI_{95\%}{}^{boot}$ [0.01; 0.56], respectively.

Personality traits. As an additional step to facilitate the interpretation of results, we tested the predictive power of personality traits over anthropomorphic attribution. We introduced the personality traits (n = 10) as predictors of the participants' anthropomorphic attribution scores in a multivariate linear regression analysis (controlling for age, gender and level of education). This approach makes it possible to measure the influence of a factor controlling for the other (covariate) factors. Surprisingly, results showed an extremely precise and coherent pattern. Indeed, either on agency, $b=0.59$, $t(94)=2.09$, $p=.041$, $CI_{95\%}[0.03; 1.15]$, sociability, $b=0.64$, $t(94)=2.43$, $p=.018$, $CI_{95\%}[0.11; 1.16]$, or animacy, $b=0.48$, $t(94)=2.10$, $p=.039$, $CI_{95\%}[0.03; 0.95]$, the higher the self-evaluated orderliness trait (e.g., "Like order") the higher the anthropomorphic attributions. Results showed that sociability attributions were also predicted by open-mindedness, (e.g., "Try to identify the reasons for my actions"), $b=0.40$, $t(94)=2.89$, $p=.005$, $CI_{95\%}[0.13; 0.69]$. Finally, on disturbance attribution, the enthusiasm trait (e.g., "Have a lot of fun"), $b=-0.52$, $t(94)=-2.56$, $p=.013$, $CI_{95\%}[-0.93; -0.12]$, and sociability attribution (e.g., "Enjoy being part of a group"), $b=0.40$, $t(94)=2.14$, $p=.036$, $CI_{95\%}[0.03; 0.78]$, proved to be significant predictors.

2.3 Discussion

The first experiment aimed to test a 2 × 2 anthropomorphic tendency/appraisal matrix (low/high anthropomorphism x negative/positive appraisal) and its relation to personality traits as a mediator of the influence of phenotypes on anthropomorphic attribution.

First, regarding the 2 × 2 matrix, the results did not confirm the hypothesis and showed an appraisal difference only for high anthropomorphizers. This result could be explained (1) by an intrinsic neutrality for low anthropomorphizers considering robots as mere neutral objects, (2) by a lack of variability in the data due to an insufficient sample size. Indeed, with a 2 × 2 matrix, it is likely that the likelihood of belonging to one of the phenotypes is not equivalent between each phenotype. In line with the second explanation, we observed, despite the normal distribution of each cluster, there were size differences between clusters (i.e., ncluster1 = 45, ncluster2 = 31, ncluster3 = 19). It could be because in the present paradigm we used a social psychology approach for power analysis based on the number of comparisons in the analysis of cluster. However, this type of power analysis could not include the entropy differences between clusters (i.e., variance of probability of participants' cluster belonging) which is not possible to anticipate. Entropy could have result in artificially lowering down the number of clusters due to covariance. Therefore, in Experiment 2 we increased the sample size to address this issue.

In contrast to Kaplan [7], who demonstrated that extroversion, modulated anthropomorphic attributions, we found that orderliness was a main factor explaining anthropomorphic attributions and mediated anthropomorphic phenotypes. Extraversion was related specifically to the attribution of sociability traits. This particular result may be explained by the social motivation for people with high level of extraversion to attribute social characteristics and competence to other agents (i.e., sociability dimension of the HRIES [18]). This explanation is at the core of Epley and colleagues' framework [1]. Therefore, we could assume that orderliness would pertain to the cognitive process of increasing the predictability of non-human agents, while the extraversion could be related to the motivation to find a social agent, and as such, an incentive to see other agents as viable social agents, ascribing them social competences.

Interestingly, orderliness (as a conscientiousness dimension) has been related to personality constructs such as the need for cognition [22] and the need for closure [23]. These dimensions have proven to be significant predictors of attributions of human characteristics [4]. Therefore, in the second experiment we investigated these two dimensions of need for closure and need for cognition. The objective was to delineate the different component of orderliness as the main personality trait influence on anthropomorphism tendency in Experiment 1.

3 Experiment 2

As humans, we are specialized in understanding what it is like to be a human and we may use this representation of ourselves (as a starting point for induction) to have a rough understanding of what it is like to be another human [24]. However, facing non-human agents, we have to engage in more cognitively demanding processes to switch from a readily accessible human representation (anthropomorphism) to an alternative representation. Employing these processes are intrinsically dependent on our willingness to engage in such a cognitively effortful activity. The individual tendency to engage in a cognitively demanding process is called the "need for cognition" [25]. In the context of anthropomorphism, the use of alternative (non-anthropomorphic) representations whilst facing a non-human agent, would be proportional to the likelihood of engaging in effortful processing [1, 26].

On the other hand, Epley and colleagues and others [1, 2] propose that anthropomorphism could be a readily accessible strategy for reducing the contextual complexity and uncertainty of an environment. Facing non-human agents for which we do not have alternative non-anthropomorphic models would be one of these uncertain and uncomfortable situations [27]. However, our strategy to deal with this uncertainty greatly varies from one individual to another. The Need for Closure concept was introduced to develop a theoretical framework for this cognitive-motivational aspects of decision making [28, 29]. Webster and Kruglanski [30] proposed a five-dimension taxonomy of the "need for closure" trait including (1) the *need for order*, the preference for structure and avoidance of disorder. (2) the *need for predictability*, as the preference for secure and stable knowledge. (3) the *need for decisiveness*, as the search for clear decision making. (4) the *discomfort toward ambiguity*, as the negative experience in ambiguous situations; and (5) the *close-mindedness*, as the unwillingness to challenge one's own knowledge by alternative opinions or inconsistent evidence. People with a high need for closure tend to ground their reasoning on more accessible information rather than to engage in an effortful thinking process [31] and are therefore more likely to anthropomorphize robots, as anthropomorphism is an "easier" strategy to make sense of the environment [4].

Therefore, extending our 2 × 2 anthropomorphism tendency/appraisal matrix hypothesis, we propose that anthropomorphic phenotypes could also interact with the individual traits of high vs. low need for cognition and need for closure.

3.1 Method Experiment 2

Participants. Participants were 166 males and 343 females (Mage = 22.43, SD = 9.03) recruited online on Prolific. The sample size was increased in experiment 2 (compared to experiment 1) in order to have a sufficient large sample for the clustering. As discussed in experiment 1, we expect differences in clusters' entropy (referring here to the differences in probability for participants to belong to a specific cluster). These differences could impair the test of our 2 × 2 anthropomorphism tendency/appraisal hypothesized matrix. The reason is that clusters need to reach a size threshold to emerge in the analysis.

Procedure. Participants were instructed to fill out a list of questionnaires. First, they completed the Efficient Assessment of Need for Cognition [32] and the short version of the Need for Closure scale [33]. The order of questionnaires was counterbalanced between participants. Second, participants were asked to evaluate anthropomorphic characteristics of an iCub robot presented on the screen on the HRIES scale (see Experiment 1). For each questionnaire, items were presented in a random order.

Material. *Need for cognition.* We administered the Efficient Assessment of Need for Cognition[32] with a positive dimension that assesses the need for cognition (e.g., "I would prefer complex to simple problems") and a negative dimension that assesses the aversion for cognition (e.g., "Learning new ways to think doesn't excite me very much"). For each item, participants rated whether they agreed or disagreed with the statement on a scale from 1 "totally disagree" to 7 "totally agree".

Need for closure. Participants also completed the short version of the Need for Closure (NFC) scale [33] (which is based on the full NFC scale [30]). The scale includes five items representing various ways in which NFC is expressed. The five items are: need for order (e.g., "I enjoy having a clear and structured mode of life"), need for predictability (e.g., "I dislike unpredictable situations"), need for decisiveness (e.g., "When I have made a decision, I feel relieved"), discomfort toward ambiguity (e.g., "I don't like situations that are uncertain"), and closemindedness (e.g., "I do not usually consult many different opinions before forming my own view"). For each item, participants rated whether they agreed or disagreed with the statement on a scale from 1 "totally disagree" to 7 "totally agree".

3.2 Results

Anthropomorphism phenotypes. To evaluate the reliability of phenotypes in anthropomorphism, we conducted a two-step clustering [20] using Disturbing, Agency, Sociability, and Animacy measures to classify participants according to anthropomorphic patterns [21]. The clustering developed a solution with a 4 clusters' matrix with a 1.65 ratio sizes (Table 2) and a cluster quality = 0.4 (fair fit).

Compared to Experiment 1, the higher sample size allowed for finer-grained clustering. Results showed that the disturbance attributions delineated a positive appraisal cluster (clusters 1 and 3) from a negative appraisal cluster

Table 2 First cluster solution. Centroids in function of cluster and factors. Factors are presented by order of importance for the clustering solution from left to right

		Agency		Sociability		Animacy		Disturbance		N
		μ	σ	μ	σ	μ	σ	μ	σ	
Cluster	1	3.37	0.83	2.23	0.96	2.10	0.77	3.79	1.13	91
	2	3.28	0.89	3.23	1.23	2.74	0.84	6.34	0.59	149
	3	4.77	0.67	4.04	0.99	3.62	0.88	4.80	0.96	150
	4	5.17	0.59	6.47	0.89	4.38	1.01	6.52	0.47	119
	Combined	4.18	1.12	3.82	1.51	3.27	1.19	5.47	1.33	509

(clusters 2 and 4). In each of the two clusters a group of low "anthropomorphizers" (clusters 1 and 2) and a group of high "anthropomorphizers" (clusters 3 and 4) emerged. An ANCOVA analysis (controlling for age, gender, education level, and their level of knowledge about robots) showed that clusters can be distinguished based on the agency, $F(3, 508) = 199.54$, $p < .001$, $\eta^2_p = .54$, animacy, $F(3, 508) = 144.76$, $p < .001$, $\eta^2_p = .46$, disturbance, $F(3, 508) = 283.23$, $p < .001$, $\eta^2_p = .63$, and (conversely to experiment 1) sociability, $F(3, 508) = 186.57$, $p < .001$, $\eta^2_p = .53$, dimensions. Contrasts were processed with planned comparisons with the following coding: cluster 1 (low anthropomorphism/positive appraisal), cluster 2 (low anthropomorphism/negative appraisal), cluster 3 (high anthropomorphism/positive appraisal), cluster 4 (high anthropomorphism/negative appraisal) [-0.5, -0.5, 0.5, 0.5; -0.5, 0.5, -0.5, 0.5; 0.5, -0.5, -0.5, 0.5] to test the (2) positive/negative appraisal x (2) high/low anthropomorphism pattern (and with respect to orthogonal contrasts set) [34]. Results showed that the contrast comparing the low vs. high anthropomorphizers was significant on animacy $t(505) = 19.80$, $p^{boot} = 0.001$, $\eta^2_p = .44$, $CI_{95\%}[1.42; 1.74]$, agency, $t(505) = 24.13$, $p^{boot} = 0.001$, $\eta^2_p = .54$, $CI_{95\%}[1.51; 1.78]$, sociability, $t(505) = 21.56$, $p^{boot} = 0.001$, $\eta^2_p = .47$, $CI_{95\%}[1.84; 2.21]$, and disturbance, $t(505) = -8.07$, $p^{boot} = 0.001$, $\eta^2_p = .11$, $CI_{95\%}[-0.73; -0.45]$. The second contrast comparing the positive vs. negative appraisal clusters was also significant on animacy $t(505) = 8.71$, $p^{boot} = 0.001$, $\eta^2_p = .13$, $CI_{95\%}[0.54; 0.85]$, agency, $t(505) = 2.36$, $p^{boot} = 0.021$, $\eta^2_p = .01$, $CI_{95\%}[0.03; 0.30]$, sociability, $t(505) = 12.96$, $p^{boot} = 0.001$, $\eta^2_p = .25$, $CI_{95\%}[1.03; 1.40]$, and disturbance, $t(505) = -29.22$, $p^{boot} = 0.001$, $\eta^2_p = .63$, $CI_{95\%}[-2.28; -2.00]$. The control contrast was significant on all dimensions ($p^{boot} < 0.01$) except animacy ($p^{boot} = 0.447$). These contrasts show that the high anthropomorphism cluster attributes disturbance to robots to a lower extent than the low anthropomorphizers. However, note that the effect sizes on each dimension vary with respect to the anthropomorphism vs. disturbance focus contrast. The reason for this overlap in results could be explained by a positive/negative bias (associated to the disturbance attributions). Instead of a mere disturbance attribution to robots, the disturbance could be driven by prior sensitive attributes. This influence of prior attitudes could be stronger on this HRIES dimension than the three others (see [18]). We conducted a control analysis on the first contrast controlling for disturbance attributions. Despite a slight decrease of effect sizes, the results on animacy (η^2_p = .38), agency (η^2_p = .52) and sociability (η^2_p = .38) remained significant (all $p_s < 0.001$). Still, as the contrasts proved to be significant, they confirm the 2×2 matrix hypothesis (Fig. 2).

Interaction between anthropomorphic phenotypes and need for cognition/closure. First, to ease the analysis and clarity of results we clustered participants on "need for cognition" and "need for closure" dimensions. Doing so, we were able to delineate homogenous groups of participants on each dimension. The clustering analysis showed a 2 clusters solution (low vs. high) for the need for cognition (cluster quality = 0.60, ratio of sizes = 1.19) and the need for closure (cluster quality = 0.40, ratio of sizes = 1.24), see Tables 3 and 4.

Second, we processed a MANCOVA introducing the anthropomorphic attributions as DVs, the anthropomorphic, need for cognition, need for cognition clusters as IVs (including the interaction terms $4 \times 2 \times 2$) and the aforementioned covariates. Results showed that participants high in need for cognition attributed more agency, $F(1, 508) = 4.24$, $p = .040$, $\eta^2_p = .01$, $CI_{95\%}[0.01; 0.29]$, and less disturbance, $F(1, 508) = 6.04$, $p = .014$, $\eta^2_p = .01$, $CI_{95\%}[-0.33; -0.04]$, to the robot. Main effects on the need for closure showed only a significant difference between clusters on agency attributions, $F(1, 508) = 4.56$, $p = .033$, $\eta^2_p = .01$, $CI_{95\%}[0.01; 0.29]$. Participants high in need for closure attributed more intentionality to the robot. Interestingly, while we did not find any significant interaction between anthropomorphic clusters and need for cognition clusters, the need for closure and anthropomorphic clusters revealed significant interactions on agency, $F(3, 508) = 3.14$, $p = .025$, $\eta^2_p = .02$, sociability, $F(3, 508) = 3.07$, $p = .028$, $\eta^2_p = .02$, and disturbance, $F(3, 508) = 5.64$, $p = .001$, $\eta^2_p = .03$, attributions. Contrasts analyses (with Bonferonni correction) showed that the effect of the need for closure was mainly on the anthropomorphic cluster 1 (low anthropomorphism/positive appraisal) either on agency, $F(1, 490) = 8.83$, $p = .003$, $\eta^2_p = .02$, $CI_{95\%}[0.17; 0.83]$, sociability, $F(1, 490) = 4.88$, $p = .028$, η^2_p = .01, $CI_{95\%}[0.06; 0.97]$, or disturbance, $F(1, 490) = 11.39$, $p = .001$, $\eta^2_p = .02$, $CI_{95\%}[-0.96; -0.25]$, attributions (Fig. 2).

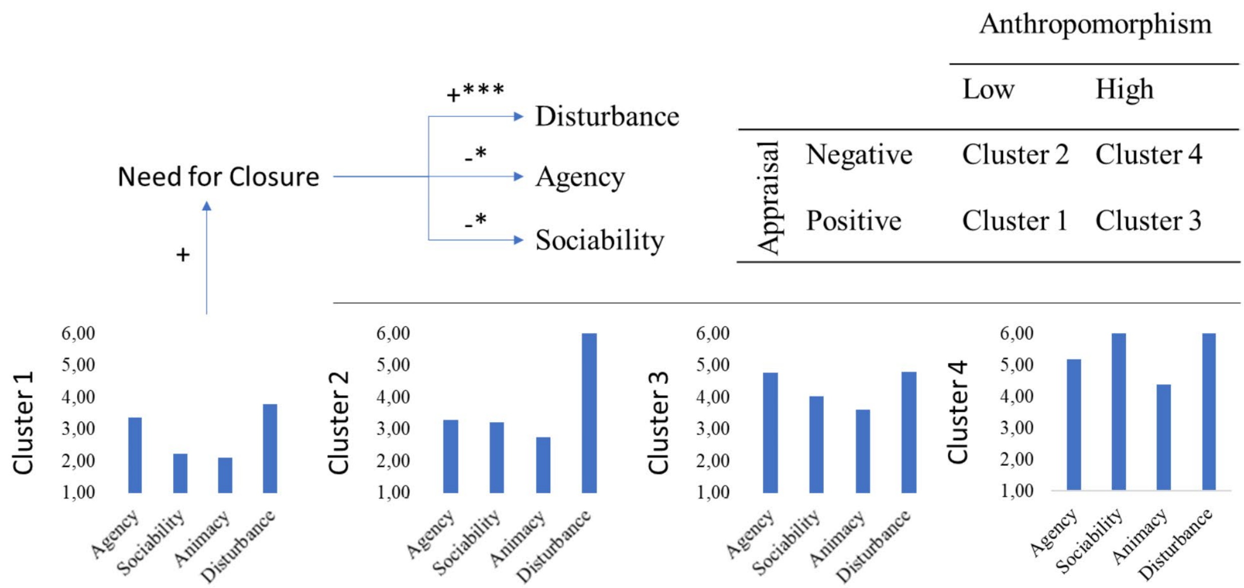

Fig. 2 Anthropomorphism/Appraisal phenotypes and effect of Need for Closure trait on attributions. Low anthropomorphizers who are high in need for closure show more disturbance, and lower agency, and sociability attributions than participants low in need for closure

Table 3 Need for cognition clusters

		Need for cognition		Aversion for cognition	
		μ	σ	μ	σ
Cluster	1	3.64	1.04	3.40	0.76
	2	5.26	0.88	1.76	0.69
	Combined	4.44	1.26	2.59	1.10
Statistics		$F(1,508) = 342.56$, $p < .001$, $\eta^2p = .40$		$F(1,508) = 641.01$, $p < .001$, $\eta^2p = .56$	

Low anthropomorphizers who are high in need for closure show more disturbance, lower agency, and lower sociability attributions than participants low in need for closure.

3.3 Discussion

The second experiment investigated the interaction between the 2 × 2 anthropomorphism matrix and the need for cognition/closure dimensions. Results showed an anthropomorphism tendency (low/high)/appraisal (negative/positive) matrix resulting in different patterns of anthropomorphic responses. Our results showed that while the need for cognition, as a significant positive predictor of attributions, remained independent from the cluster solution, the need for closure interacted with the anthropomorphic clusters, especially for low anthropomorphizers with a positive appraisal of robots[1]. Therefore, we could propose that this particular cluster (low anthropomorphism/positive appraisal) gathers people with a low level of (positive/negative) expectations about robots. We posit that without prior representation or attitudes toward robots, more general cognitive influence (e.g., negative attitudes because of expectations) would be likely to occur [1].

[1] Due to our analysis strategy we may exclude the potential explanations by age, gender, level of education or knowledge about robots.

4 General Discussion

In the present study, we propose that the imaginative form of anthropomorphism could be considered as a phenotype, related, at least in part, to individuals' personality traits. Our results provide evidence in favor of phenotypes based on a high vs. low tendency to anthropomorphize robots and a negative vs. positive appraisal. This demonstrates that individuals associate appraisal with their anthropomorphic perception, despite the neutrality (in terms of appraisal) of the cognitive process of anthropomorphism per se. In other words, while anthropomorphism is defined as the attribution of human characteristics to non-human agents, these inferences contain the positive/negative attitudes one has about those observed agents [1, 4].

Therefore, these phenotypes could help explain a part of the variability in terms of reactions toward robots and especially the interindividual differences facing anthropomorphic robots such as the sensitivity to the uncanny valley [35]. The uncanny valley theory posits that the more similar an android robot is to a human being, the more monstrous its imperfections appear to us [36]. However, it is important to mention that we do not consider the clusters as purely

Table 4 Need for closure clusters

Cluster		Order		Predic.		Decisiv.		Ambig.		Closem.	
		μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
	1	5.02	1.28	5.31	0.83	5.43	0.98	3.3	1.27	5.89	0.56
	2	3.39	1.29	3.35	1.21	4.36	1.09	2.3	0.98	4.02	1.15
	Combined	4.12	1.5	4.2	1.44	4.84	1.173	2.78	1.22	4.86	1.38
Statistics		$F(1,508)=202.99$, $p<.001$, $\eta^2p=.29$		$F(1,508)=441.01$, $p<.001$, $\eta^2p=.47$		$F(1,508)=127.64$, $p<.001$, $\eta^2p=.20$		$F(1,508)=93.24$, $p<.001$, $\eta^2p=.16$		$F(1,508)=398.76$, $p<.001$, $\eta^2p=.44$	

dichotomous but as two continuums closer to the concept of "trend" rather than "category".

Interestingly, the interplay between anthropomorphic phenotypes and personality traits, while significantly present, remains limited to low anthropomorphizers despite both being related to anthropomorphic attributions. We could refer to Epley and colleagues framework to explain the limited result [1]. For low anthropomorphizers, anthropomorphism would only occur if the situation requires it, such as during an uncertain situation involving a non-human target. In this context the need for closure as cognitive-motivational aspects of decision making to deal with uncertainty may trigger anthropomorphic attributions [28, 29]. However, this phenomenon would be true only for individuals who do not engage in anthropomorphism thinking before facing the non-human target in an uncertain situation. Based on Fisher's distinction between imaginative and an interpretative anthropomorphism [2], we can postulate that for low anthropomorphizers, who have a high need for closure, anthropomorphism is primarily interpretive and situation-dependent (i.e., "state-anthropomorphism"). Conversely, for high anthropomorphizers, anthropomorphism is primarily imaginative as a trait-anthropomorphism is less impacted by the situation than prior representations. In other words, the tendency to consider non-human agents as anthropomorphic could be considered a trait, which is influenced by other personality traits such as the need for closure [1, 4]. However, defining the tendency to anthropomorphise non-human agents only in reference to the need for closure or cognition (which subsequently leads to uncertainty reduction processes)[1] does not (1) explain why people attribute anthropomorphic characteristics to agents presented on pictures nor (2) that imaginative and interpretative anthropomorphism may be related (controlling for need for closure or need for cognition traits) [4].

Considering these phenotypes could also be interesting to further understand human-robot interactions. Indeed, as constitutive elements of the personality of an individual, they may contribute causally to the development of attitudes and behaviors toward robots [3]. In the present study we hypothesized a matrix including anthropomorphism and appraisal. We indeed found an orthogonal relationship between the two dimensions. Therefore, we may consider insufficient to evaluate only positive or negative attitudes (e.g. Negative Attitudes Toward Robot scale [37]) or interpretative anthropomorphism (e.g. Godspeed questionnaire [38], Robotic Social Attribute Scale [39], Human–Robot Interaction Evaluation Scale [40]) because positive or negative attitudes may be related to high or low anthropomorphism but the opposite is also true. Subsequently, describing behavioral responses of people toward robots based on attitudes or anthropomorphism in isolation has a limited predictive power. Therefore anthropomorphism and attitudes toward robots should always be concomitantly measured and modeled.

5 Limits and Future Research

A first limitation to recognize is that, if we posit that anthropomorphism can be considered a trait and that phenotypes can be delineated, we cannot and do not assume that anthropomorphism is not also context dependent. Thus, even if one is more inclined to anthropomorphize than the other, the situation may have a profound impact on the process. Thus, anthropomorphic phenotypes can only be considered a reference point for a tendency rather than a true predictor of anthropomorphism in a specific situation. In other words, phenotypes must be considered in interaction with the direct environment in which one is inclined to anthropomorphize an agent. Further studies will need to relate these phenotypes to the types of behavioral responses in HRI.

Second, in the present study, participants evaluated an iCub robot. This robot is part of the iconic corner of Duffy's triangle of anthropomorphism, which encompasses robots employing a minimal set of (facial) features that nevertheless manage to be expressive [41]. The other two corners are the human corner, which aims to replicate human characteristics, and the abstract corner, which is about mechanistic functional design. Our clustering was based on an iconic robot, which means that our phenotypes relate to this robot type. If we can assume a generalization to the human type with respect to the tendency to anthropomorphize and, as such, the validity of our phenotypes to explain a tendency to anthropomorphize these "human" robots [4], "abstract" robots could inhibit all anthropomorphic inferences, resulting in no difference between phenotypes.

Third, although these results are promising, they should be cross-referenced with other measures. Here, we used HRIES but other tools might be useful to ensure that phenotypes are related to the whole concept of anthropomorphism or to specific sub-dimensions.

Finally, we cannot guarantee that our results are not culturally dependent and that our model could be valid in a cross-cultural context. Indeed, the semantics behind the concept of anthropomorphism might be different in Western and East Asian cultures for example. Thus, the intersection of the dimensions of evaluation and anthropomorphism might not be relevant or at least not be interpreted in the same way. Indeed, attitudes towards robots do not follow the same philosophy in Western and East Asian cultures [42, 43].

6 Conclusion

Anthropomorphism is a central process in human-robot relations. It is through this cognitive process that we define a representation of these artificial agents and the sets of behaviors that we will be able to produce towards them. However, this process is not homogeneous between observers and where some see only a plastic assembly, others naturally see social agents. In this paper we have proposed to structure representation phenotypes on the basis of a tendency to anthropomorphism and appraisal. The results highlight the need to consider both the representation and the associated valence. The study also highlights the need to adapt the robots to the humans who will interact with them. In the case of social robots, there is a significant probability that in contexts such as helping the elderly or learning, which are targets of development, we find these different phenotypes. Therefore, we can consider that for a person who will be assisted by a social robot to take medication or to move, the anthropomorphic phenotype can explain a large part of his perception of an interaction experience that will have been mostly standardized. For students, the impact of phenotype on the effectiveness of robot-assisted learning also appears to be critical. By taking into account the anthropomorphic phenotype of these people, we open the possibility to better define the modalities of interactions and the types of signals that trigger anthropomorphism. In the same way that we adapt socially to our human interlocutors to facilitate interactions and that we have learned to respect the representations of others, it is crucial to integrate this adaptive dimension to human-robot interactions and this inevitably requires a better understanding of human psychology in these situations.

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