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Robot Humanization Measure/Task

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Abstract

In human-robot interaction, one key factor to predict and understand how human engage and interact with robots is how the inter-individual differences in how they perceive, consider and feel toward robots. Building on the theories of social categorization and dehumanization we aimed to develop a new tool assessing the perceived conceptual distance between humans and robots when observing robotic actions. In three studies we developed and validated the structure of a task aiming at evaluating to what extent individuals humanize robots. In this task participants were required to judge the human-likeness of robotic actions on a robot/human continuum represented by silhouettes. In a fourth study, we adapted this new tool to a decision task (with two response options robot/human) in which response time and response selection are used to infer the robot humanization bias of participants. Results showed reliable psychometric structure of the present measure in both questionnaire and decision task format. We further discuss how social categorization bias in HRI may be relevant to better predict attitudes toward robots.

Keywords: Human-robot interaction; Social categorization; Dehumanization; Measurement; Social robotics

1. Introduction

In human-robot interaction, individuals vary in how they perceive, consider or even feel toward robots. These differences are attributable to a range of dispositional, contextual, developmental and cultural factors [6,18,64,77]. To better understand, predict how human-robot interaction (HRI) evolves, it is crucial to assess these inter-individual differences in robot representation, as they may have strong behavioural consequences [55,69]. Most of research investigate this issue through the prism of attitudes –the "state of mind" of a person or a group towards an object, an action, another individual or group– [56] or anthropomorphism –the attribution of human characteristics to non-human animals or objects– [3,8,66]. However, these measures only evaluate to what extent one has developed a specific attitude (e.g. I would feel uneasy if robots really had emotions) or how one ascribes certain human-like characteristics (e.g. warmth). While these measures are informative to evaluate general attitudes, they neglect fundamental psychosocial processes such as (social) categorization that consists in categorizing agents into differentiated groups and acknowledging a (conceptual) distance between them [4,33,53,72,75]. This fundamental phenomenon of human psychology is not based on specific attributions, but rather on a comparison between concepts and mental representation of groups (e.g. human group vs robot group) [21,68] and is central to explain human social interactions with other humans [40,45,46] or with robots [41,69]. Here we propose to develop a new easy-to-use measure to evaluate this perceived conceptual distance between robots and humans.

1.1. From anthropomorphism to humanization

Recent results demonstrate that when thinking about artificial agents, such as robots, individuals not only attribute human characteristics (i.e. anthropomorphism) to them but also represent them on a conceptual continuum from robots to humans [20,68]. In social psychology, this continuum has been theorised by Haslam as the dehumanization [31,32]. This process explains how an individual or a group of individuals could be perceived as less human or even non-human under certain conditions. Two types of dehumanization have been proposed by the author: 1) animal dehumanization and 2) mechanistic dehumanization. Of lesser interest for the present purpose, animal dehumanization refers to considering another human as an animal. Of key interest for the present paper, mechanistic dehumanization refers to considering another human as an automaton and can lead to physical abuses, psychological violence or even slavery.

In other words, (de-) humanization is a concept related to the balance between humans and representation of another entity as non(or less)-human. On the other hand, as much as humans can be dehumanized, artifacts can be represented as being close to a human category (humanization) [64].

In the context of this assumed process of "humanization", researchers [65,67,69], have shown that the measure of the humanization continuum was explained phenomena of robotic social presence[1] better than the concept of anthropomorphism. In other words, addressing how humans perceive robots might be better conceptualized in the context of social categorization than attribution of human-like features (anthropomorphism). In a series of experiments [65,67,69], participants had to interact verbally with a robot or to describe it. The results showed a social presence effect only after the participants were engaged in a verbal interaction with the robot. The use of anthropomorphism scale [3,8] and an adapted humanization measure based on Haslam framework [31] demonstrated that the effects were mediated by the dynamics of (social) categorization –(de)humanization scale– rather than anthropomorphic attributions [65,67]. These results argue for the importance of the social categorization component in how robots are represented in HRI. Social categorization processes that are admittedly correlated, but distinguishable, from anthropomorphism [64]. Humanization might presume anthropomorphism, as it would imply acceptance of robots as social agents on a continuum between humans and non-human entities. Humanization would be an attitude that goes one step further than anthropomorphism, which is a more general process of attribution of human-like characteristics to non-human entities [16,31,32,45].

1.2. Aim of study

In the present series of studies, we developed a task that addresses humanization by measuring the conceptual distance between robot/human categories when observing robotic actions. By doing so, we aimed to provide the first measure of the "robot humanization process" in HRI. Our study aimed also at addressing another issue related to existing tools measuring human attitudes towards robots, namely the issue of language.

A major issue in the existing tools measuring anthropomorphic attributions to robots is their lack of generalizability across various languages. Indeed, most of the present measures require

[1] The modulation of cognitive performance in presence of another agent [2,74].

participants to evaluate to which extent adjectives are corresponding to one or several robots (i.e. interpretative anthropomorphism). For example, the Godspeed questionnaire [3] requires participants to judge a robot on different bi-dimensional scales such as “artificial” to “life-like” continuum. The Robot Social Attributes Scale [8] or the Human-Robot Interaction Evaluation Scale [66] presents adjective such as “uncanny” or “intentional”. The material provided by Marchesi et al [49] use complex opposite mentalistic (e.g. “iCub was trying to cheat by looking at opponent’s cards.”) and mechanistic (e.g. iCub was unbalanced for a moment) descriptions on a bi-dimensional scale. On the imaginative anthropomorphism side (i.e. detached from concrete perception), the Individual Differences in Anthropomorphism Questionnaire [80] requires participants to express, according to them, “to what extent does the average robot have consciousness”. All these scales suffer the same issue: it is difficult, if not impossible, to accurately translate all these items in all languages, especially with the same associated semantic representation. Therefore, cross-cultural comparison becomes a challenge. This is even more evident if we consider how important are the cultural norms’ influencing the human mind and the need to take these influences into account in the generalization of the human psychological phenomena (involved in HRI) [73].

In order to circumvent the difficulty of language use in tools measuring attitudes towards robots, we designed a task that provides a unique scale for visual scenarios without using language that could be used uniformly across countries and cultures. The task builds on Marchesi et al. items [49] that require participants to evaluate the actions of a robot in terms of human- or robot-likeness. We designed a scale to evaluate human-likeness of a robot action, which displays robot and human silhouettes at each of its extremes (see Figure 1).

To address the aims of our study, we designed four experiments:

Experiment 1 aimed at providing a reliable psychometric structure (Exploratory Factor Analysis) to the task (Robot Humanization Measure, RHM**)** we designed that measures humanization process, based on the previously developed tool by Marchesi and colleagues [49].

Experiment 2 aimed at confirming the results from Experiment 1 (Confirmatory Factor Analysis).

Experiment 3 aimed at providing an easily accessible paper-pen version of the test by adapting the Robot Humanization Measure (RHM) to a 7-point Likert scale.

Experiment 4 aimed at developing a robot humanization tendency measurement tool in the form of a decision task taking into account implicit and explicit measures.

2. Experiment 1

The first experiment aimed to design a structure for the Robot Humanization Measure (RHM). To this end, we used scenarios of the Instance Test, depicting the humanoid robot in various daily activities [49]. However, instead of using mentalistic or mechanistic vocabulary of Marchesi et al. (2019), each scenario included a scale with a "robot" and a "human" silhouette on each extreme, as presented in Figure 1.

2.1. Method

The participants were 340 Italian speakers recruited online (M_{age} = 26.32 years, SD = 7.13, 175 males, 156 females and 9 non-declared) on Prolific. The sample size was determined by the recommendation in exploratory factor analyses literature (EFA). In EFA, based on the number of items (q = 34), Schreiber and colleagues [62] recommend 10 observations resulting in a minimum of 340 required participants.

First, participants had to complete the 34 items of the Instance Test [49], with the difference from the original version of using silhouettes (robot, human) rather than sentences. Each item of IST was composed of a scenario with three pictures involving iCub depicted in daily activities and two responses silhouettes and a 100-point slider between the two silhouettes (one was positioned on the left, and the other one on the extreme right of the scale) (Figure 1). The position of the silhouettes was kept constant within participants, as recommended by Maeda who showed that unidirectional response options were more reliable in online-administered questionnaires [48]. Also, unidirectional response options significantly decrease the likelihood of misresponses (i.e. an inconsistency in response to a target item relative to reference items) compared to bidirectional response options [81]. However, the position of silhouettes was counterbalanced between participants to control for the left-side response option selection bias (i.e. the tendency to select response options located on the left side [54]. The order of presentation of the items was randomized.

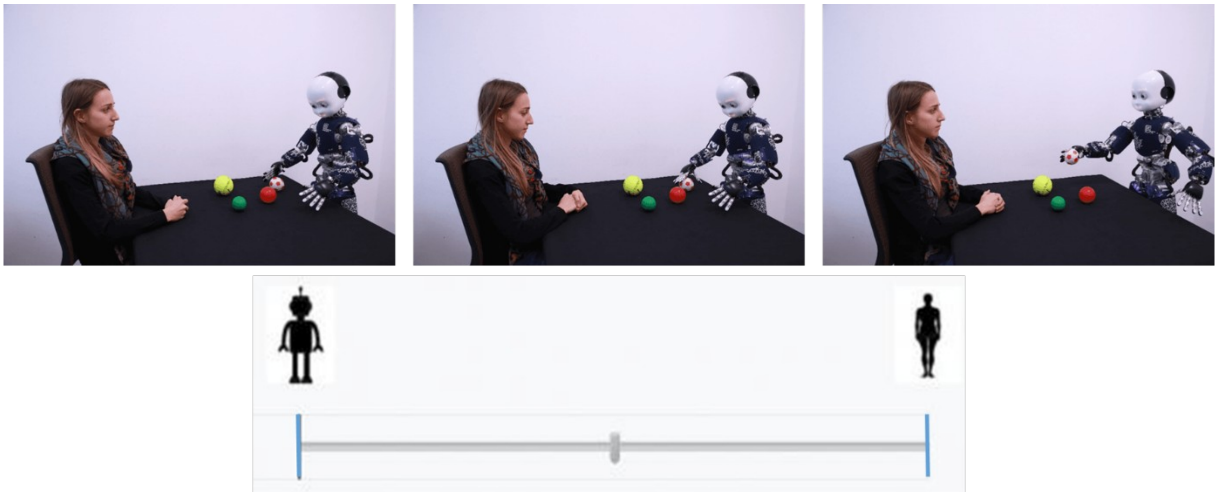

Figure 1. Scenario example

In each item, participants were explicitly instructed to move the slider on the bipolar scale toward the silhouette that according to them represented best the degree of human-likeness of the depicted robot action. The cursor was initially always placed at the centre of the scale (i.e., the null value).

Anthropomorphism. At the end of the experiment, participants also evaluated the iCub robot on the Human-Robot Interaction Evaluation Scale (HRIES) [66]. The scale consists in four sub-dimensions including Sociability (e.g., Warm, α = .83), Agency (e.g., Self-reliant, α = .77), Animation (e.g., Alive, α = .70), and Disturbing (e.g., Creepy, α = .80). The interest of this scale is that it makes possible to evaluate robots on a broad spectrum of anthropomorphic attributions and included the de-humanization items from Haslam framework in its development [31], especially in the Agency dimension that refers to the mechanistic/human nature dehumanization dimension. For each dimension, participants rated whether they agreed or disagreed (from 1 to 7) to attribute related characteristics to the robot being present. (i.e., “For each trait, you will have to evaluate whether, according to you, it corresponds or not to the robot that is presented to you.”). For each trait on each robot, a 7-points slider scale was presented from 1 “not at all” to 7 “totally”.

2.2. Results

Three participants were excluded from analysis because they did not respond to all items.

Sample data

First, the inter-item correlation was assessed using a Bartlett's sphericity test, $\chi^2(496) = 2048.07$, $p<.001$. Inter-item correlations evaluate the extent to which one item is related all other items in a scale [60,83]. Second, we conducted a Kaiser-Meyer-Olkin (KMO) test that assesses that the partial correlations of each pair of items are low once the linear effect of the other items has been controlled, which would confirm the presence of latent factors linking the items to each other [83]. Its value varies from 0 to 1.1. This index measures the quality of the sample data for the factor analysis. Here the KMO = .80. KMO values between .80 and 1.00 indicate the sampling is adequate [9,17,35].

Analysis method

We performed an exploratory factor analysis to determine the initial factorial structure of the measurement tool. Also we spotted and excluded unsuitable items. The latent factors were identified using common factor model. Compared to other component models (e.g. PCA), this method provides more reliable results in the majority of the cases, while, in the remaining cases, the methods would be, at least, roughly equivalent [26,63,78,82,84]. We choose a maximum likelihood extraction method with 1 (hypothesized) factor.

Selection of items

First, we conducted an exploratory factor analysis (EFA) including all items with the assumption of a loading on one common factor (i.e. Humanization factor). We followed a Churchill-like procedure to optimize the information extraction [10]. The process was as following: we included all items in a scale reliability analysis. To maximize the Cronbach's alpha we evaluated the reliability of the factor considering the change of the alpha indices if an item was dropped [14,76], for similar procedure see [66]. As an iterative process we conducted a new EFA with the remaining items until we reached a stable alpha. The purpose was to maximize the amount of information provided by each items in order to save the reliability of the construct (quality) while optimizing the number of items (quantity). Indeed, to ensure a good measure, it must be acknowledge that questionnaire length is negatively correlated with the quality of participants' response and the completion of questionnaires [51] especially in self-administered measures [25,50]. We were able to keep a Cronbach alpha higher than .70 (Cronbach, 1951; Hair, Black, Babin, & Anderson, 2010) losing the minimum of information. Dropping 12 items did not impair the internal consistency of the scale. The Cronbach alpha remained equal to .87. We then conducted a new factorial analysis (using the same settings) to confirm the stability of the psychometric structure of the sample data after each item exclusion.

However, it is noteworthy that such a process reduces the width of the construct to its conceptual centroid. We assume this practical choice to ensure a good balance between practicability (quantity) and reliability (quality). From the 34 original experimental items, 22 remain in the final matrix, $\chi^2(231) = 2379.65$, $p<.001$; $KMO = .89$, explaining 55.64 % of the variance (Table 1).

Table 1. Study 1 pattern matrix presenting loading factors for each item, percent of explained variance.

Items	Factor	Items	Factor
Item 4	.649	Item 21	.493
Item 25	.648	Item 26	.493
Item 12	.629	Item 17	.486
Item 14	.614	Item 18	.476
Item 35	.608	Item 8	.475
Item 13	.549	Item 20	.466
Item 9	.543	Item 16	.458
Item 22	.509	Item 32	.443
Item 27	.505	Item 34	.441
Item 28	.496	Item 2	.435
Item 7	.495	Item 29	.433

The table 2 presents the descriptive statistics of the current measure.

Table 2. Descriptive statistics of the Robot Humanization Measure

Descriptive statistics						
	N	Mean	SE	Average SD	Cronbach *a*	Number of items
Robot Humanization Measure	340	55.17	0.69	19.28	0.89	22

Correlation to anthropomorphic measure

To evaluate the external validity of the present task's factor we correlated the measure to the scores from the HRIES. Results are presented in table 3. The Robot Humanization Measure was significantly correlated to the dimensions of the HRIES (all $p_s < .05$) except for disturbance dimension.

Table 3. Correlation matrix between the Humanization factor and the HRIES dimensions.

		Sociability	Human-likeness	Agency	Disturbance
Humanization	Pearson rho	.248	.235	.183	-.094
	p value	< .001	< .001	.001	.082

2.3. Discussion

The first study aimed to determine a psychometric structure of the Robot Humanization Measure (RHM) tool, which was based on Marchesi et al. scenarios [49] and psychosocial theories [18,31]. Factorial analysis of the first study confirmed a one-factor structure, as hypothesized. Results showed good internal consistency with a Cronbach's alpha equal to .89, based on the 22 items of the final matrix. Also, the Robot Humanization Measure was significantly correlated to anthropomorphic attributions assessing the content validity [43]. As theorized, Humanization of robots is related intertwined (albeit distinct, as shown by the low rho values) with anthropomorphism [18,64].

3. Experiment 2

In the second experiment, we aimed to confirm the psychometric structure of the Robot Humanization Measure found in Experiment 1. We therefore, repeated the procedure of Experiment 1, but included only the items from final matrix of Experiment 1.

1.1. Method

The participants were 220 Italian speakers recruited online (M_{age} = 26.90 years, SD = 8.59, 115 males, 101 females and 4 non-declared). The sample size was determined by the recommendation in exploratory factor analyses literature (EFA). In EFA, based on the number of items (q = 22) resulting in a minimum of 220 required participants [62].

The procedure was similar to Experiment 1. Participants had to complete the 22 items extracted from Experiment 1. Participants were instructed to move the slider on the bipolar scale toward the silhouette that according to them represented best the degree of human-likeness of the depicted robot action. . As in Experiment 1, the cursor was initially always placed at the centre of the scale (i.e., the null value). The position of the silhouettes was kept constant in order to ease participants' responses but counterbalanced by participants. The order of presentation of the items was randomized.

Anthropomorphism. At the end of the experiment, participants also evaluated the iCub robot on the Human-Robot Interaction Evaluation Scale (HRIES) (Spatola, Kühnlenz & Cheng, 2020) that includes four sub-dimensions including Sociability (e.g., Warm, α = .76), Agency (e.g., Self-reliant, α = .78), Animation (e.g., Alive, α = .70), and Disturbing (e.g., Creepy, α = .81).

2.4. Results

The table 4 presents the descriptive statistics of the experiment 2 Robot Humanization Measure.

Table 4. Descriptive statistics of the Robot Humanization Measure (experiment 2).

Descriptive statistics						
	N	Mean	SE	Average SD	Cronbach a	Number of items
Robot Humanization Measure	220	53.51	12.32	18.88	0.89	22

Confirmatory factor analysis

Using AMOS plugin in SPSS, we conducted a confirmatory factor analysis (CFA) with a structural model (figure 3) to test the reliability of the factor identified in study 1 [39,47,85]. We used a variance-covariance matrix with maximum likelihood (ML) estimation [52]. ML estimation is widely used and has proved to be more reliable in many case than others [5]. The model-fit indices showed that chi square ($\chi 2$) value was 183.19 (df = 165, p = .158). Table 5 shows the model-fit indices [36,61] as well as the recommended thresholds [85].

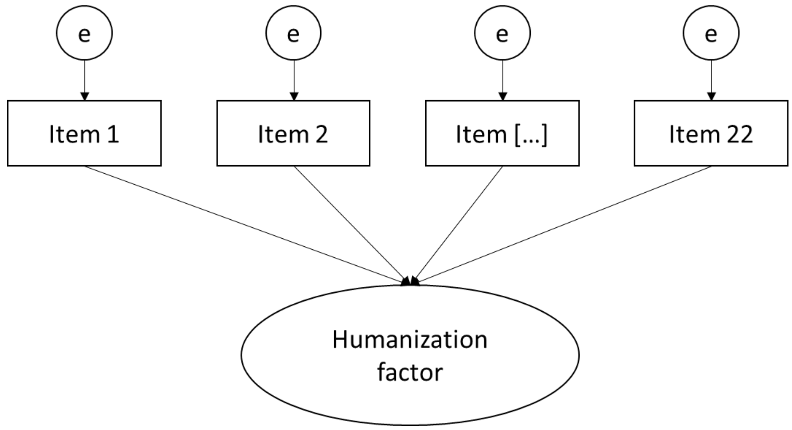

Figure 2. Confirmatory factor analysis model

Table 5. Confirmatory model fit indices. χ^2/df the ratio of chi square to degree of freedom; NFI the normalized fit index, CFI the comparative fit index; Tucker–Lewis index (TLI); root mean square error of approximation (RMSEA); SRMSR the standardized root mean square residual.

	Recommended value	Values obtained
χ^2/df	≤ 3.00	1.11
NFI	≥ .90	.90
CFI	≥ .90	.99
TLI	≥ .90	.98
RMSEA	≤ .08	.02
SRMR	≤ .09	.04

As shown in Table 3, all model-fit indices exceeded their respective common threshold of acceptance. The table 6 presents the non-standardized estimates for each item associated to their common factor (all $p_s < .001$). The Cronbach's alpha was also reliable ($\alpha = .89$).

Table 6. CFA non-standardized estimates

Items	Estimate	S.E.	t value	p value
Item 2	.823	.129	6.363	<.001
Item 4	.851	.148	5.744	<.002
Item 7	.971	.163	5.969	<.003
Item 8	.903	.165	5.485	<.004
Item 9	1.015	.164	6.203	<.005
Item 10	1.046	.176	5.943	<.006
Item 13	1.192	.194	6.157	<.007
Item 14	1.311	.199	6.59	<.008
Item 16	.685	.134	5.105	<.009

Item 17	.986	.152	6.493	<.010
Item 18	.794	.169	4.698	<.011
Item 20	.909	.172	5.279	<.012
Item 21	.864	.169	5.108	<.013
Item 22	1.068	.189	5.647	<.014
Item 25	1.095	.173	6.345	<.015
Item 26	1.006	.178	5.657	<.016
Item 27	.765	.153	4.997	<.017
Item 28	.613	.145	4.223	<.018
Item 29	1.080	.189	5.699	<.019
Item 32	1.335	.23	5.803	<.020
Item 34	.783	.17	4.597	<.021
Item 35	1.214	.191	6.363	<.022

External validity

Similarly to Experiment 1, to test the generalizability of the present tool with respect to the evaluation of other robots, we correlated the Robot Humanization Measure with the anthropomorphic attributions in the HRIES scale. We conducted Pearson correlation analyses including HRIES dimensions (Disturbance, Agency, Sociability and Animacy factors) and the Robot Humanization scores. Analyses showed a relation between RHM scores and HRIES positive attributions (Agency, Sociability, and Animacy). Results are presented in table 7.

Table 7. Correlation matrix between the Robot Humanization score and the HRIES factors.

		Sociability	Human-likeness	Agency	Disturbance
Humanization	Pearson rho	.270	.356	.212	-.012
	p value	.000	.000	.002	.854

2.5. Discussion

Experiment 2 aimed to confirm the structural validity of the Robot Humanization Measure tool. The structural model for the CFA showed a good fit with the 22 items. In addition, results again confirmed the external validity (anthropomorphic attributions).

4. Experiment 3

In order to design an easy to use a paper-pen version of the Robot Humanization Measure, we adapted the RHM to a 7-point Likert scale. The choice of the 7-point Likert scale was motivated by studies showing maximal reliability for the paper-pen format [24,57,58]. Symonds has suggested that reliability is optimized with 7-points scale [70], and this has been supported by other research (for a review see Colman, Norris, & Preston, 1997). Lewis also found stronger correlations with t-test results using 7-point scales [44] considered as an optimum for accurate responses [57]. We hypothesized that the structure of the RHM should be reliable with the 7-points Likert scale and, similar to Experiment 1, participants' scores on the RHM should be correlated with the HRIES scores (in particular Agency and Sociability dimensions, Human-likeness being pertaining to the design and therefore more descriptive process than relying on a social categorization).

4.1. Method

Participants were 222 Italian speakers recruited online on Prolific. The sample size was determined by the recommendation in exploratory factor analyses literature (EFA).

Participants completed the 22 items of the RHM presented in random order on a 7-point Likert scale ranging from -3 to +3 with one silhouette at each extremity. The position of the silhouette was counterbalanced by participants. They also completed the HRIES scale to measure anthropomorphism with the Sociability (e.g., Warm, $\alpha = .80$), Agency (e.g., Self-reliant, $\alpha = .77$), Animation (e.g., Alive, $\alpha = .70$), and Disturbing (e.g., Creepy, $\alpha = .85$).

4.2. Results

The table 8 presents the descriptive statistics of the experiment 3 Robot Humanization Measure.

Table 8. Descriptive statistics of the Robot Humanization Measure (experiment 3). The mean is recoded on a 1 to 7 point scale (instead of the original -3 to +3) for the purpose of clarity.

Descriptive statistics

	N	Mean	SE	Average SD	Cronbach *α*	Number of items
Robot Humanization Measure	220	4.43	.04	1.31	0.82	22

Confirmatory factor analysis

The CFA followed the same procedure as study 2. The model-fit indices showed a $\chi 2$ value equal to 207.53 (df = 179, p = .071). Table 9 shows the model-fit indices [36,61] as well as the recommended thresholds [85].

Table 9. Confirmatory model fit indices.

	Recommended value	Values obtained
χ^2/df	≤ 3.00	1.16
NFI	$\geq .90$	.81
CFI	$\geq .90$	.97
TLI	$\geq .90$	.96
RMSEA	$\leq .08$	.03
SRMR	$\leq .09$	.05

As shown in Table 9, all model-fit indices exceeded their respective common acceptance threshold. The table 10 presents the non-standardized estimates for each items. All items were significantly associated with their common factor (all $p_s < .001$). The Cronbach's alpha was also reliable ($\alpha = .82$).

Table 10. CFA non-standardized estimates

Items	Estimate	S.E.	t value	p value
Item 2	.542	.156	3.478	<.001
Item 4	1.808	.524	3.451	<.001
Item 7	1.142	.403	2.838	.005
Item 8	1.621	.498	3.256	.001
Item 9	1.435	.441	3.251	.001
Item 10	1.949	.555	3.511	<.001
Item 13	1.500	.469	3.199	.001
Item 14	1.882	.555	3.388	<.001
Item 16	.930	.317	2.932	.003
Item 17	.961	.341	2.822	.005
Item 18	1.374	.469	2.93	.003
Item 20	1.252	.416	3.007	.003
Item 21	1.477	.465	3.178	.001
Item 22	1.786	.525	3.403	<.001
Item 25	1.76	.516	3.414	<.001
Item 26	1.935	.567	3.414	<.001
Item 27	1.186	.411	2.882	.004
Item 28	1.160	.403	2.875	.004
Item 29	1.701	.537	3.168	.002
Item 32	1.650	.522	3.162	.002

Item 34	1.401	.452	3.097	.002
Item 35	1.823	.493	3.696	<.001

Correlation to anthropomorphic measure

Again, to evaluate the external validity of the present task's factor, we correlated the measure with the scores from the HRIES. Results are presented in table 11. The Humanization factor was significantly correlated to the dimensions of HRIES (all $p_s < .05$).

Table 11. Correlation matrix between the Humanization factor and the HRIES dimensions.

		Sociability	Human-likeness	Agency	Disturbance
Humanization	Pearson rho	.386	.366	.218	-.151
	p value	< .001	< .001	.001	.025

1.1. Discussion

Experiment 3 aimed to test and provide a practical version of RHM, which could be administered not only in a computerized version but also as on paper. . Indeed, the use of a 100-points slider may be difficult to use in a paper-pen format or to quantify responses. Based on literature recommendation about scale practicability [24,57,58,70], we tested a 7-point Likert scale format that proved to be reliable with respect to its internal (CFA) and external validity.

We, therefore, recommend the use of the 7-points Likert scale for paper-pen format or low sample sizes, in order to avoid the noise in data due to the range of the 100-points slider that could be detrimental especially for between-subject designs (e.g. equality of variances).

5. Experiment 4

In Experiment 4, we aimed to adapt RHM to a decision task format in order to address more implicit cognitive processes involved in evaluation of robots. There are two forms of measures of cognitive processes: explicit and implicit [19]. Explicit measures operate on a conscious level and are generally extracted through explicit self-reports (e.g. questionnaires), while implicit attitudes rely on unconscious and more automatic processes, and are typically assessed via implicit measures (e.g. reaction time paradigms, implicit association test) [34]. Explicit measures are usually more practical and flexible than their implicit counterparts while implicit measures might constitute better predictors of future intentions and behaviours [42], and thus be more representative of real attitudes than explicit declarations, which can be influenced by, for example social desirability bias [59].

In Experiment 4, we developed a decision task (study 4) according to the theories of spreading activation in semantic networks [12]. According to this theory, in decision task (a task that requires to judge stimuli according to two or more alternative choices), variations in response time depend on the extent to which two stimuli are semantically related. When a stimulus and a particular response are associated, this particular response becomes more accessible (facilitation) [23]. The facilitation from semantic associations is also conceptualized as occurring outside of conscious awareness, relying on implicit processes, and it is assumed to be an involuntary and perhaps unconscious phenomenon [15]. Thus, it differs from direct retrieval based on explicit memory and can be used to measure implicit cognition [27,30].

In Experiment 4, we intended to provide a discrete measure using response times that could quantify semantic associations in a more implicit and automatic manner (compared to continuous measures, without time constraint). The basic procedure involves measuring how quickly people classify stimuli (i.e. the robot's actions) in one or another category (i.e. robot vs human). Decision tasks (e.g. Implicit Association Test, see [27,28]) have been used in social psychology literature to investigate biases in racial groups, gender, sexuality, age, and religion, as well as assessing self-esteem. Therefore, this approach might also be taken to measure categorization and, as an extension, the humanization bias.

In addition, we aimed to evaluate the stability of RHM when repeating the stimuli. In most of the decision tasks (e.g. Stroop task, Flanker task, Implicit Association Test), stimuli are presented multiple time in order to provide a reliable average of participants' response tendencies. Therefore, we designed the paradigm in four test blocks and evaluated the stability of participants' biases across blocks.

5.1. Method

Eighty-four participants were recruited online on Prolific (M_{age} = 27.71 years, SD = 9.53, 46 males, 31 females, 2 others and 5 non-declared). The sample size was determined—as recommended by Tabachnick and Fidell [71]—on the basis of the desired power (.80), alpha level (.05), for univariate regression, and medium anticipated effect size. Using G*Power 3.1 [22], the minimum required sample size was calculated as 64.

Participants were asked to evaluate the human-likeness of the robot actions by pressing the S or L key on their keyboard. Following a 500 ms fixation cross, the scenario was displayed for 3000 ms, then the response keys appeared at the bottom of the screen for 3000 ms or until participant response (figure 3). Participants evaluated each of 88 items in 4 consecutive blocks of 22 trials. Within each block the side of the response keys was counterbalanced (i.e. 11 "human/robot" and 11 "robot/human"). Between each block, the position of response was also counterbalanced per block: If an item was presented in the previous block with a "human/robot" response pattern, it would then be associated to a "robot/human" response pattern in the following block.

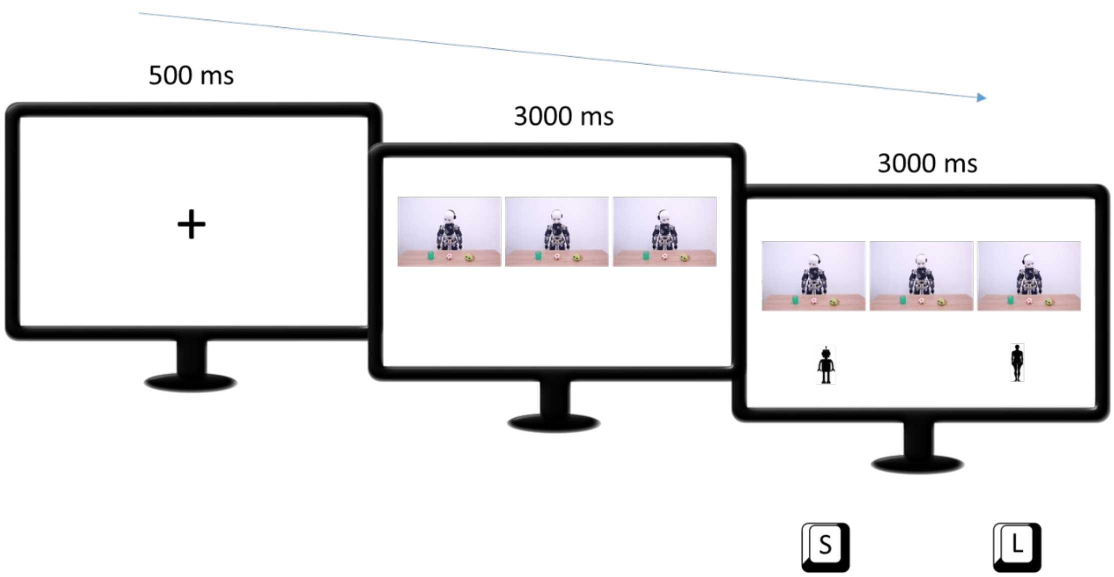

Figure 3. Timeline of an experimental trial.

Interpretative anthropomorphism. Again, participants evaluated the iCub robot on the Human-Robot Interaction Evaluation Scale (HRIES) [66] that includes four sub-dimensions Sociability (e.g., Warm, α = .88), Agency (e.g., Self-reliant, α = .80), Animation (e.g., Alive, α = .80), and Disturbing (e.g., Creepy, α = .80).

5.2. Results

Preliminary analyses. The data from three participants were discarded because they did not respond respond to at least 70% of the items in one or several blocks. Trials with a reaction time (RT) lower than 150 ms were considered outliers and then removed from RT analyses, which corresponded to 151 trials (2.12% of the trials).

Humanization score computation. Humanization score was computed as follows:

$$\text{Humanization score} = (z_{\text{robot}} - z_{\text{human}}) \text{ x } p_{\text{human}}$$

Participants' response times were divided and averaged with respect to the choice of the participants (i.e. "robot" vs "human" response). 2) For each participant, the "robot" RT and "human" RT were standardized by subtracting the overall average RT of participants. 3) The "human" RT standardized score was subtracted from the "robot" RT standardized score to compute a difference score. 4) Finally, to take into account the "human/robot" proportion of response, the difference score (step 3) was multiplied by the proportion of "human" response. The advantage of such score is to take into account both the interindividual variability in response times and the proportion of participants' responses. The overall score represents a standardized time to select the "human" answer (or participant's humanization bias). The higher the score, the higher the humanization bias. The table x presents the descriptive statistics of the humanization score. Table 12 presents the descriptive statistics. A t-test showed that the sample did not present a humanization bias, $t(80) = -.09$, $p = .931$, $CI_{95\%}$ [-19.25, 17.64].

Table 12. Descriptive statistics of the Humanization score, the proportion of "human" response, the response time to select the robot answer and the response time to select the human answer.

	Descriptive statistics	
	Mean	SD
Humanization score	-0.81	83.42
p_{human}	0.47	0.18
RT robot	983 ms	234 ms
RT human	992 ms	219 ms

Block

To test the reliability of the present measure across blocks we conducted a mixed linear model including the computed Humanization score (computed for each of the four blocks) as a dependent variable, the blocks (1, 2, 3, 4) as an independent variable and the participants as a random factor. Results showed no significant differences, $t(80) = -.38$, $p = .593$, $CI_{95\%}$ [-11.36, 22.77], all contrasts (with Bonferonni correction) showed a $p > .50$.

We conducted additional analyses to test whether the non-significance of the block variable was due to a lack of significance or evidence for the null hypothesis. We conducted Bayes factor analyses using the JASP software [79] on the effect of blocks on humanization bias. A Bayes factor (BF) quantifies the amount of evidence for a hypothesis, compared to an alternative hypothesis. It provides an indices estimating how much the data of a sample are more likely to support an hypothesis or an alternative one [37,38]. A *BF* superior to 3 is accepted as a positive weight of evidence indicating that one hypothesis is 3 times more likely than its alternative counterpart. Results showed a *BF* of 60.97 in favour of the null hypothesis. In other words, in our data, the null effect is 60.97 times more likely than the absence of an effect arguing for the stability of the measure across blocks (figure 4).

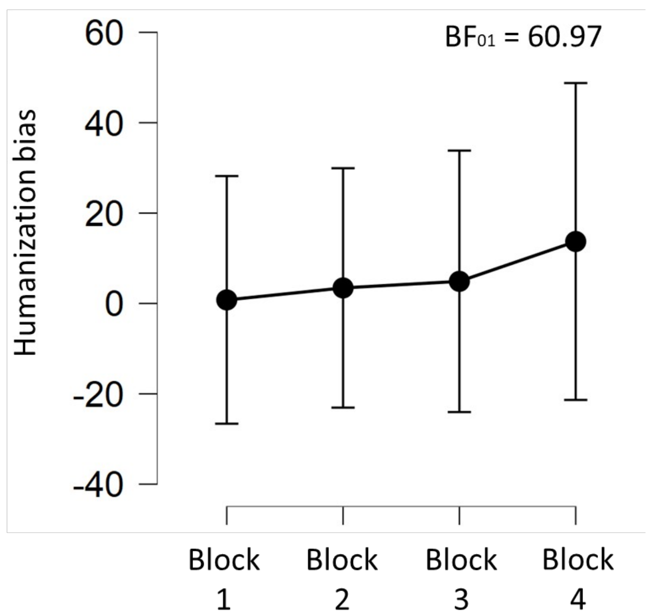

Figure 4. Humanization bias as the function of the blocks

Correlation to anthropomorphic measure

Similar to previous results, to evaluate the external validity of the present task we correlated the RHM with the scores from the HRIES. Results are presented in table 13. Interestingly, the humanization score was significantly correlated <u>only</u> to the Agency dimensions of the HRIES (*p*

= .015) that collects concepts referring to intentionality, the main contrasting feature in the Mechanistic/Human dimensions of Haslam dehumanization framework [31].

Table 13. Correlation matrix between the Humanization score and the HRIES dimensions.

		Sociability	Human-likeness	Agency	Disturbing
Humanization score	Pearson rho	.103	-.066	.268	-.137
	p value	.359	.559	.015	.226

It is important to mention that the difference score, ($z_{\text{robot}} - z_{\text{human}}$) or the proportion of "human" response (p_{human}) taken in isolation were not correlated to the Agency attributions (r = -.18, p = .103; r = .17, p = .137) arguing for the need to take into account both RT and proportion of response information in the humanization score.

5.3. Discussion

Experiment 4 aimed to test the generalizability of the RHM to a decision task. The RHM appears to be feasible, and a reliable and valid measure of Haslam mechanistic (de-)humanization dimension [31]. The results also showed a reliability and stability of the measure across block repetition.

The advantages of this decision task version compared to the standard measure is the use of response times as discrete measures and the test-retest by blocks which makes it possible to display the same items repeatedly. Importantly, we evaluated the paradigm with 4 repetitions. While not significant, the trend from block analysis points toward an increase of the humanization bias after several repetition. One hypothesis is that seeing the same scenario repeatedly participants stop to process the "physical content" (e.g. the robot) and tend to focus more on the "semantic content" (e.g. the story, the action) triggering more mentalistic attribution. Another hypothesis would be that the more participants see the robot, the more they consider it as familiar and categorize it as closer to them [1,29]. Further studies might aim at evaluating longer versions of the task.

6. General discussion

Understanding how humans cognitively represent robot agents is one of the grand challenges of social robotics [86]. Human interactions depend on fundamental socio-cognitive processes, such as categorization. Categorization of entities is fundamental, as it simplifies perception and cognition related to the environment by defining representative structures according to perceived differences or similarities. If we aim to develop robots to (socially) interact with humans, we need to understand how these artificial agents are (socially) categorized by humans.

Building on social-categorization theories [7,21,31] we developed a tool that measures the humanization bias in representing robots. The "humanization" terminology refers to the continuum between the Robot and the Human. This approach provides a new perspective by referring to the evaluation of robots to the definition of the humanity and the human "self". In other words the robot humanization bias relates to the question "to what extent is the robot different from me?". In psychological terms, we could rephrase this question in "how far is the robot from my group of belonging?". The four studies presented here provide the first tool to assess this conceptual distance that we named the robot humanization bias. Measuring the level of ethnocentric view of robotic agents based on the humanization continuum we could better understand the human attitudes towards robots.

7. References

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