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Attitudes Towards Robots Measure (ARM): A New Measurement Tool Aggregating Previous Scales Assessing Attitudes Toward Robots

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Abstract

In the forthcoming decade, interactions between humans and robots are expected to increase gradually. The attitudes that individuals hold towards robots will play a pivotal role in predicting their behavior towards these novel artificial agents, as well as their acceptance across multiple societal pillars. Despite the significant impact of attitudes on the success of human-robot interactions, no existing measure of attitudes towards humanoid robots currently meets the rigorous psychometric standards, particularly in terms of the percentage of variance explained. In this study, we introduce a new measure of attitudes towards robots (ARM), building upon previous scales on the topic, and provide evidence for the scale's internal and external validity. Through three experiments, we selected the most reliable items pertaining to attitudes towards robots (derived from previous attitudes towards robots' questionnaires), identified common factors, and tested the internal and external validity of the newly developed measure. Our findings reveal 15 items, underlying attitudes towards robots, divided into three primary factors: prior anxiety, prior acceptability, and prior anthropomorphism. We report the development and validation of the scale, and discuss the identified dimensions in relation to the literature on human-robot interactions and the psychology of robot perception.

Keywords Attitudes toward robots · Human-Robot Interaction · Scale · Social robotics

1 Introduction

Recent market insights on the Humanoid Robot Market project a growth of 32% in the use of robots from 2020 to 2025. The Asia-Pacific region, North America, and Europe are expected to be the primary beneficiaries of the introduction of humanoid robots into challenging sectors such as healthcare, learning, manufacturing, defense, and security, to name a few [1]. However, the success of this process will depend largely on how well the robots are perceived and accepted by humans, with individuals' attitudes toward robots at the core [2–5].

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1.1 Current Questionnaires

To date, several studies on human-robot interaction (HRI) have demonstrated that there are significant variations in individuals' beliefs about robots [6–9], willingness to engage with them [10–13], and the types of behavior they display towards them [14–16]. As with human-human interactions [17], these differences are largely influenced by prior attitudes [18]. Therefore, accurately assessing future users' attitudes towards these new artificial agents is crucial in predicting the success of their introduction into different areas of human society and their likelihood to be accepted.

To date, despite alternatives [3], attitudes towards robots have primarily been evaluated through explicit measures, mainly self-reports. These measures include the Negative Attitudes Toward Robot scale [19, 20], the Ethical Acceptability Scale [21], the Multi-Dimensional Robot Attitudes Scale [22], the Technology-Specific Expectations Scale [23], the Frankenstein Syndrome Questionnaire [24], the

Trust Perception Scale-HRI [25], the Self-Efficacy in Human-Robot-Interaction Scale [26], and the questionnaire from the public attitudes towards robots report mandated by the European commission [27]. This abundance of questionnaires aligns with Krägeloh and colleagues' [28] assertion that it is crucial to assess the acceptability of robots in light of the increasing prevalence of socio-interactive robots. However, in their recent review [28], the authors emphasized that "currently, the evidence of factor structure and other psychometric indicators for acceptability measures is either very limited or inconsistent.“ Psychometric indicators are information that can be used to specify and estimate latent constructs and ensure the internal and external consistencies of a measurement tool. Therefore, in the current study, we aim to address this limitation by developing a new measure of attitudes towards robots with appropriate psychometric performance.

"Our experiment is based on six of the eight questionnaires mentioned earlier, excluding the Trust Perception Scale-HRI [25] and the Self-Efficacy in Human-Robot-Interaction Scale [26]. The Trust Perception Scale-HRI [25] primarily focuses on attributions or anticipation of attributions in HRI. Therefore, the measure's emphasis is on how individuals explain contextual stimuli, whereas attitudes (the phenomenon under scrutiny here) involve the evaluative process of what is being described and are more general [29]. The Self-Efficacy in Human-Robot-Interaction Scale [26], on the other hand, contains items that have already been included in other questionnaires used in our experiment. Including this questionnaire would have resulted in an artificial addition of items, requiring an extended sample size for reliable analyses.“

The *Negative Attitudes towards Robots Scale* (NARS) [19] evaluates attitudes towards robots and comprises three subscales: (1) Negative Attitudes towards Situations of Interaction with Robots (6 items; e.g., 'I would feel uneasy if I were given a job where I had to use robots'); (2) Negative Attitudes towards Social Influence of Robots (5 items; e.g., 'I would feel uneasy if robots actually had emotions'); (3) Negative Attitudes towards Emotions in Interaction with Robots (3 items; e.g., 'I would feel at ease talking with robots'). Despite its widespread use in HRI research, the NARS suffers from several psychometric limitations, including poor reliability of some items [30, 31] and limited validity of the factor structure, particularly in cross-country comparisons [32, 33].

"The *Ethical Acceptability Scale* (EAS) [21] assesses the ethical acceptability of using robot-enhanced therapy for children with autism. It comprises three subscales: 1) Ethical Acceptability for Use (5 items); 2) Ethical Acceptability of Human-like Interaction (4 items); and 3) Ethical Acceptability of Non-human Appearance (3 items). However, since six out of twelve items relate specifically to therapy for children with autism, we did not include them in our experiment. Instead, we incorporated the following 6 items: 'It is ethically acceptable to utilize social robots in healthcare' (subscale 1); 'It is ethically acceptable for children to form attachments to social robots' and 'It is ethically acceptable to create social robots with a human-like appearance' (subscale 2); and 'It is ethically acceptable to create social robots that resemble objects', 'It is ethically acceptable to create social robots that resemble imaginary creatures', and 'It is ethically acceptable to create social robots that resemble animals' (subscale 3).“

The *Multi-Dimensional Robot Attitudes Scale* (MDRAS) [22] is a comprehensive tool for assessing attitudes towards robots, covering 12 subscales. These include Familiarity (5 items, e.g., 'The introduction of a robot to my home would make me feel as though I had a new family member'), Interest (7 items, e.g., 'I would take pride in having a robot in my home'), Negative Attitudes (5 items, e.g., 'It would be regrettable to have a robot in my home'), Self-efficacy (4 items, e.g., 'I possess sufficient skills to operate a robot'), Appearance (7 items, e.g., 'I believe that robot design should be aesthetically pleasing'), Utility (5 items, e.g., 'Robots are useful'), Cost (3 items, e.g., 'I consider robots to be cumbersome'), Variety (3 items, e.g., 'I believe that robots should produce a range of sounds'), Control (3 items, e.g., 'I believe that a robot could recognize and respond to me'), Social support (3 items, e.g., 'I expect my family or friends to instruct me on how to use a robot'), Operation (2 items, e.g., 'Robots can be operated remotely'), and Environmental Fit (2 items, e.g., 'I am concerned that robots may not be suited to the current layout and furniture of my room'). The focus of this scale is on domestic robots, which limits its applicability for evaluating general attitudes beyond this specific context.

The *Technology-Specific Expectations Scale* (TSES) [23] evaluates individuals' pre-interaction expectations of robots. It includes ten questions, with five items assigned to the Capabilities subscale (e.g., 'I anticipate being able to interact with the robot') and five items allocated to the Fictional View subscale (e.g., 'I anticipate the robot possessing superhuman abilities'). However, this list of items was not validated as a scale in and of itself (i.e., no EFA or CFA was conducted).

The *Frankenstein Syndrome Questionnaire* (FSQ) [24] is designed to gauge attitudes towards humanoid robots, including acceptance, expectations, and anxieties. The name of the scale alludes to the historically prevalent Western aversion to humanoid robots [34]. The questionnaire comprises four subscales: Anxiety Toward Humanoid Robots (13 items, e.g., "The development of humanoid robots is a sacrilege against nature"), Apprehension Toward Social

Risks of Humanoid Robots (5 items, e.g., “If humanoid robots cause accidents or problems, individuals and organizations involved in their development should provide adequate compensation to those affected”), Trustworthiness for Developers of Humanoid Robots (4 items, e.g., “I have faith in the individuals and organizations involved in the development of humanoid robots”), and Expectation for Humanoid Robots in Daily Life (5 items, e.g., “Humanoid robots can create novel forms of interaction between humans and between humans and machines”). Like NARS, the scale only focuses on emotional content.

The *European Commission Attitudes Toward Robots report* (ECATR) [27], commissioned by the Directorate-General for Information Society and Media (INSFO) and coordinated by the Directorate-General for Communication (DG COMM “Research and Speechwriting” Unit), comprises nine questions, with five questions specifically targeting attitudes towards robots. These particular questions include: “Robots are beneficial to society because they assist people,“ “Robots displace people from their jobs,“ “Robots are necessary because they can perform jobs that are too difficult or dangerous for humans,“ “Robots are a type of technology that necessitates careful management,“ and “Extensive use of robots can create job opportunities.“ Despite being used in 27 EU countries in 2012, the associated report is purely descriptive and lacks any psychometric analyses or validations.

1.2 Important Priors to Define Attitudes Toward Robots

The literature on human-robot interaction has extensively examined various factors that influence attitudes towards robots. Attitudes can be defined as a mental state towards an object, an agent, or an action, and are shaped by experience, observation, learning, and social factors [35]. They predispose individuals to act in a certain way and are crucial in explaining behavior when encountering new agents, including both humans [36] and robots [37]. Attitudes are constructs, such as feelings, associated with objects, such as robots. Importantly, attitudes are multifactorial, meaning that they depend on and result from various retroactive inputs and outputs.

After reviewing various questionnaires for this study [20–22, 24, 27, 38], we have identified three key dimensions that may be related to attitudes towards robots. Firstly, anxiety towards robots may increase negative attitudes towards them. Secondly, prior acceptance - as demonstrated through interest and willingness to interact - of robots appears to fuel positive attitudes. Finally, the prior representation of robots as more or less anthropomorphic, meaning the attribution of human characteristics, may deeply influence attitudes towards robots and potentially interact with the first two factors.

1.2.1 Anxiety

A significant proportion of the population declare anxiety towards robots, particularly in regards to the potential loss of jobs [39, 40] or even a surge [6], sparking a debate about their impact on human societies [41]. Anxiety has been found to be a reliable predictor of attitudes, as it biases people in their reasoning about an anxiety-provoking agent through a negative lens. Previous studies have shown that anxiety towards an unfamiliar place can increase the perceived dangerousness of that place [42]. This process has been linked to five neural processes, which include inflated estimates of threat cost and probability, increased threat attention and hypervigilance, deficient safety learning, behavioral and cognitive avoidance, and heightened reactivity to threat uncertainty [43]. Furthermore, the effect of anxiety on attitudes tends to be strengthened by confirmation bias [44], where people use heuristics to simplify inferences [45], resulting in the interpretation and seeking out of information that is consistent with their beliefs and expectations [46]. Due to this negative lens and interaction with confirmation bias, attitudes tend to polarize. This process may be a coping mechanism to rationalize anxiety towards an agent, especially when little information is available about that agent. Anxiety can be a consequence of uncertainty, resulting in negative attitudes.

1.2.2 Acceptance

Acceptance is typically defined as the intention to use or the actual use of robots [24, 47, 48]. Like anxiety, acceptance is both a precursor and a consequence of attitudes. To clarify, we will refer to acceptance prior to attitudes as “prior acceptance” and acceptance after attitudes as “usage acceptance”. In the context of technology acceptance, prior acceptance refers to the interest before usage that leads an individual to form a positive perception of an object. Parasuraman proposed a framework of motivators and inhibitors of technology readiness [50] based on the Technology Acceptance Model (TAM) [49], an information systems theory that models how individuals tend to accept and use a technology. The core motivators of the model are optimism and innovativeness. In other words, interest and positive evaluation are prerequisites for acceptance [50]. Bröhl and colleagues demonstrated that the TAM framework can be applied to robot acceptance [51]. Therefore, if we seek to better predict attitudes towards robots, it is crucial to consider prior acceptance (as an optimism/innovativeness component).

1.2.3 Anthropomorphism

Anthropomorphism refers to the tendency to ascribe human characteristics to non-human entities. There are two types of anthropomorphism to consider: anthropomorphism by design, which is based on the proximity of an agent's shape to that of a human [52], and anthropomorphism by attribution, which involves observers attributing human characteristics such as emotions or intentions to an agent [53]. Fisher proposed two ways in which people engage in anthropomorphism of the latter type [54]. The first is interpretative anthropomorphism, which involves attributing human characteristics to non-human agents based on actual observation. The second is imaginative anthropomorphism, which involves developing a prior representation of non-human agents independent of sensorimotor experience [54]. According to Fisher, individuals develop an a priori representation based on an imaginative phenomenology as a function of their level of imaginative anthropomorphism, without even seeing or interacting with a non-human agent. Imaginative anthropomorphism can moderate attitudes towards these agents and shape their future evaluation or interaction with them [55], and can also affect our most fundamental cognitive processes [56–61]. From a societal perspective, the degree of anthropomorphism is predictive of how agents are considered in terms of legal protection, public interest [62], responsibility, and moral status [63]. Therefore, anthropomorphism, especially imaginative anthropomorphism, is a crucial component for predicting attitudes.

1.3 Current Study

Due to the diversity in the conceptualizations of attitudes and the need for a tool to effectively measure attitudes towards robots with a strong psychometric performance [28], we combined the items from various questionnaires [20–22, 24, 27, 38], and identified common factors that underlie attitudes towards robots. This allowed us to create an integrated tool for measuring attitudes towards robots, which we call the Attitudes Toward Robot Measure (ARM). To accomplish this, we followed the guidelines set forth by Cabrera-Nguyen [64] and Churchill [65], and selected the items of interest in Experiment 1. In Experiment 2, we conducted an exploratory factor analysis and correlated the exploratory factors with external measures of technology readiness. Finally, in Experiment 3, we evaluated the reliability of the psychometric structure through a confirmatory factor analysis, assessed the external validity of the newly created scale, and explored the connections between the identified dimensions of attitudes and the perceived anthropomorphism of robots.

2 Experiment 1: Items Selection

The primary objective of the first experiment was to diminish the number of items taken from the existing scales that measure attitudes towards robots [20–22, 27, 38], and to identify the items that have a connection with one another across these scales. In the selection process, we evaluated the items' loadings on a common factor (i.e. attitudes towards robots), and analyzed their inter-correlations.

2.1 Method

One hundred and thirty-one participants recruited via Prolific took part in the experiment (73 males and 58 females, $\mu_{age} = 36.36$, $SD = 12.45$).

The participants were asked to evaluate 111 items presented in a random order with regards to their attitudes towards robots (on a scale from 1 "not at all" to 7 "totally"). The items originated from: the Negative Attitudes Toward Robot scale [19, 20], the Ethical Acceptability Scale [21], the Multi-Dimensional Robot Attitudes Scale [22], the Technology-Specific Expectations Scale [23], the Frankenstein Syndrom Questionnaire [24] and the questionnaire from the public attitudes toward robots report mandated by the European commission [27]. Questionnaires as well as their subscales were presented in a random order. Lastly, participants completed demographic questions relating to age, gender and educational level.

3 Results

Initially, we inputted all 111 items into a correlation matrix (using Pearson's method) in accordance with the guidelines provided by Diamantopoulos and colleagues [66]. The purpose of this step was to identify all related items, that is, items correlated with a Pearson's $r > .80$ (i.e. items that are believed to measure the same construct). Six pairs of items met this threshold (Table 1). We then selected one item from each pair based on the evaluators' assessment of the items' clarity. This assessment was made through a pair-blinded decision, and both evaluators chose the same items for each pair. As a result, we were left with 105 items.

In the second phase, we utilized a maximum likelihood factoring method of extraction to conduct an exploratory factor analysis on the 105 items. The objective of this phase was to identify items that do not have a connection to each other (without considering the factorial structure). Significantly, this step ensured the optimal selection of items before factor identification, thereby increasing the potency of the analysis. Based on factor loading, we identified 48

Table 1 Pairs of items with a $r > .80$. Items in bold remained in the pool of items

Items
I expect my family or friends to teach me how to use a robot.
I expect my family or friends to advise me how to use a robot.
I would hate the idea that robots or artificial intelligences were making judgments about things
I would hate the idea that robots or artificial intelligences were making judgments about things
I trust persons and organizations related to the development of humanoid robots to disclose sufficient information to the public, including negative information.
I can trust persons and organizations related to development of humanoid robots.
It is ethically acceptable to make social robots that look like imaginary creatures.
It is ethically acceptable to make social robots that look like animals
Something bad might happen if robots developed into living beings
Something bad might happen if humanoid robots developed into human beings.
The development of humanoid robots is blasphemous.
The development of humanoid robots is a blasphemy against nature.

inter-correlated items (Table 2) with a 0.77 Cronbach's α [67].

4 Discussion

The primary objective of the first experiment was to carefully select the most relevant items that pertained to the evaluation of attitudes towards robots from the existing pool of items [20–22, 27, 38], to enable the creation of a comprehensive measurement tool with a suitable construct validity. Out of 111 items, 48 items showed inter-correlation, indicating a mutual conceptual foundation among them. As a result, these 48 items held promise for (1) the development of a scale that measures distinct dimensions of attitudes towards robots, and (2) the optimization of analysis power in the Exploratory Factor Analysis (EFA), which was conducted in the second experiment.

4.1 Experiment 2

In the second experiment, we conducted an exploratory factor analysis (EFA) to explicate the factor structure for the novel scale. It is noteworthy that the first phase of the experiment encompassed items that were both positively and negatively charged, in accordance with the assumption that attitudes toward robots can be dichotomous. Therefore, we formulated a hypothesis that the dimensions extracted will encompass both positive and negative dimensions, and that these two dimensions will display a negative correlation. As a result of the first experiment, we discovered items relevant to expectations about robots' capabilities (e.g. emotions, thought-reading) and beliefs about the use of robots (e.g. dangerous or laborious tasks) [23, 27]. Hence, we anticipated the emergence of dimensions corresponding to these two concepts.

In order to evaluate the external validity of the recently developed instrument, we examined the correlation between the newly created measure and the Technology Readiness Index (TRI) [50]. Prior studies have demonstrated that a favorable outlook on technology can indeed serve as a dependable predictor of the acceptance of a wide range of novel technologies [68], including robots [69]. Therefore, we postulated that an increased readiness for technology would correspond to more positive attitudes towards robots. Conversely, we predicted that more negative attitudes towards technology would be associated with more negative attitudes towards robots as well.

4.2 Method

Two hundred and sixty participants recruited via Prolific took part in Experiment 2 (72 males and 188 females, $\mu_{age} = 36.85$, $SD = 11.60$). The sample size was determined following the recommendations in the EFA literature (*40*). Specifically, based on the number of items (here $q = 48$), at least 5 observations (per item) are recommended [70], resulting in a minimum of 240 required participants.

Building upon research showing a positive link between technology readiness and positive attitudes toward robots [71–73], participants first completed the short version of the Technology Readiness Index (TRI) [50] with the Optimism (e.g. "Technology gives people more control over their daily lives", $\alpha = 0.75$), Innovativeness (e.g. "Other people come to you for advice on new technologies", $\alpha = 0.83$), Discomfort ("Technical support lines are not helpful because they don't explain things in terms that you understand", $\alpha = 0.66$), and Insecurity ("You do not feel confident doing business with a place that can only be reached online", $\alpha = 0.63$) dimensions. The objective was to provide an external measure without involving the "robot" semantic to provide a reliable external reliability test reference. The participants rated the items on a scale ranging from 1 "totally disagree" to 7 "totally agree". In the current experiment, the Discomfort and the Insecurity dimensions did not reach the recommended 0.70 Cronbach's alpha threshold [67]. To address this limitation, we conducted a post-hoc correlation analysis, which revealed a correlation between these two dimensions, $r = .41$, $p < .001$. This correlation suggests that the two dimensions have a shared conceptual basis (which we assume to be negative attitudes). For further analyses, we thus aggregated the two factors into one dimension which we label 'Negative Attitudes'. The aggregation of the two dimensions resulted in an 0.71 alpha.

Table 2 Inter-correlated items loading on a common factor structure

Items	Original scale
Robots are a form of technology that requires careful management	ECATR
Robots are a good thing for society, because they help people	ECATR
Robots are necessary as they can do jobs that are too hard or too dangerous for people	ECATR
Humanoid robots can be very useful for caring the elderly and disabled	FSQ
Humanoid robots can create new forms of interactions both between humans and between humans and machines	FSQ
Humanoid robots may make us even lazier.	FSQ
Humanoid robots should perform dangerous tasks, for example in disaster areas, deep sea, and space	FSQ
I am afraid that humanoid robots will encourage less interaction between humans.	FSQ
I am afraid that humanoid robots will make us forget what it is like to be human	FSQ
I am concerned that robots would be a bad influence on children	FSQ
I don't know why, but humanoid robots scare me.	FSQ
I feel that if we become over-dependent on humanoid robots, something bad might happen.	FSQ
I would feel uneasy if humanoid robots really had emotions or independent thoughts.	FSQ
If humanoid robots cause accidents or trouble, persons and organizations related to development of them should give sufficient compensation to the victims.	FSQ
Many humanoid robots in society will make it less warm.	FSQ
Persons and organizations related to development of humanoid robots are well-meaning.	FSQ
Widespread use of humanoid robots would mean that it would be costly for us to maintain them.	FSQ
I feel easy around robots because I do not need to pay attention to robots as I do to humans.	MDRAS
I feel like I also become a machine when I am with a robot.	MDRAS
I feel the necessity for robots in my daily life.	MDRAS
I have enough skills to use a robot.	MDRAS
I think a robot should have human-like shape.	MDRAS
I think a robot would obey my commands.	MDRAS
I think robots are heavy.	MDRAS
I think robots should have animal-like shapes.	MDRAS
I think robots should have various colors	MDRAS
I think robots should have various shapes.	MDRAS
I think the maintenance of a robot is difficult.	MDRAS
I think the shape of a robot should have roundness.	MDRAS
I think the voice of a robot should be like the voice of a living creature.	MDRAS
I want to tame a robot according to my preferences.	MDRAS
I would want to boast that I have a robot in my home.	MDRAS
If a robot is introduced to my home, I think my children or grandchildren will be pleased.	MDRAS
It is easy to use a robot.	MDRAS
It is unnatural for a robot to speak in a human language.	MDRAS
Robots are neo-futuristic and cutting-edge.	MDRAS
I feel that if I depend on robots too much, something bad might happen	NARS
I would feel relaxed talking with robots	NARS
I would feel uneasy if I was given a job where I had to use robots	NARS
Something bad might happen if robots developed into living beings	NARS
I think I will be able to interact with robots.	TSES
I think robots will be able to perceive what I am going to do before I do it.	TSES
I think robots will be able to read my thoughts.	TSES
I think robots will be able to recognize when I look at it or when I shift my gaze to something else.	TSES
I think robots will be more than a machine.	TSES
I think robots will be similar to robots I see in movies.	TSES
I think robots will have sense of humour	TSES
I think robots will understand my emotions.	TSES

Second, participants were presented with 48 items extracted from Experiment 1. For each of the items, they expressed their level of agreement, on a scale ranging from 1 "not at all" to 7 "totally". The items were presented in a random order.

Finally, the participants answered demographic questions relating to their age, gender and education level.

5 Results

5.1 Sampling Adequacy

The inter-item correlation was assessed using a Bartlett's sphericity test, $\chi^2(1128) = 4696.38$, $p < .001$ [74, 75]. To confirm the presence of latent factors linking the items to each other [75], we used a Kaiser-Meyer-Olkin (KMO) test. The outcome of the test is a value ranging from 0 to 1 which reflects the quality of the sample data for the factor analysis. A value between 0.80 and 1.00 indicates adequate quality [76–78]. Here the KMO value was 0.84.

5.1.1 Exploratory Factor Analysis

We first conducted an exploratory factor analysis (EFA) including all items, with a maximum likelihood extraction and a Promax rotation[1]. The Promax rotation emphasizes the differences between the high and low factor saturation coefficients by raising them to the power κ (here 4, the default value [79]). As the loadings are raised to the Kth power, they are all reduced, resulting in a simpler structure. As the absolute value of the coefficients decreases, the gap between them increases [79–81].

To optimize the extraction, we followed the Churchill-like procedure [65]. All items were included in a scale reliability analysis. We maximized the reliability of each factor considering a change of the alpha indices, if an item of the factor was dropped [67, 82] (for a similar procedure, see [83]). In an iterative process, we conducted new EFAs with the remaining items, until a stable alpha was reached. This procedure maximized the amount of information provided by each item, assuring the reliability of the construct (quality), while optimizing the number of items (quantity), a particularly important factor in self-reported measures, see [84] or [85, 86]. Cronbach alpha was kept higher than 0.70 [67]. It should be noted that the outlined procedure reduces the width of the construct to its conceptual centroid. We consider it a practical choice as it assures an appropriate balance between the practicability of the scale (quantity of items) and the reliability of the measure (quality).

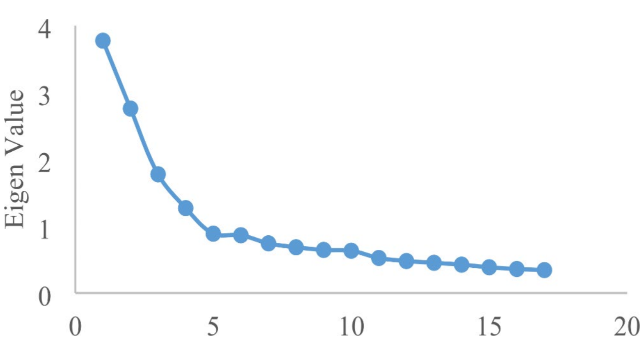

Fig. 1 Eigenvalue against the factor number

From the 48 original experimental items, 15 remained in the final matrix, explaining 56.35% of the variance (Fig. 1) across three factors (Table 3). The Goodness-of-fit Test showed a $\chi^2(74) = 97.79$, $p = .034$. However, the fourth factor embedded only two items (i.e. "Humanoid robots should perform dangerous tasks, for example in disaster areas, deep sea, and space" and "Robots are necessary as they can do jobs that are too hard or too dangerous for people") displaying a low content validity, for the seek of the scale reliability, we choose to quit this factor from the final matrix. The 15-items matrix explained 52.80% of the variance.

Finally, we integrated the three factors into a partial correlation matrix, which controlled for covariance between factors (Table 4). The findings indicated that the first factor displayed a negative correlation with the second factor, whilst it demonstrated a positive correlation with the third factor. The second factor exhibited a positive correlation with both the third and the fourth factors.

5.2 External Validity

To test the external validity of the newly created measure, we correlated each factor of the current scale with the three TRI dimensions (Optimism, Innovativeness, and the newly computed Negative Attitudes dimension) controlling for participants' age, gender and educational level (Table 5). The results confirmed our hypothesis: the first factor "Prior anxiety" (e.g. "I am afraid that humanoid robots will make us forget what it is like to be human") negatively correlated with Optimism (TRI), and positively correlated with Negative Attitudes (TRI). The second factor "Prior acceptance" (e.g. "I would want to boast that I have a robot in my home.") positively correlated with Optimism and Innovativeness (TRI) factors. The third factor "Prior anthropomorphism" (e.g. "I think robots will understand my emotions.") positively correlated with Negative Attitudes (TRI).

[1] Using orthogonal rotation (e.g. VARIMAX), we preserve the independence of the factors. With oblique rotation (e.g. OBLIMIN, PROMAX), we break it and factors are allowed to correlate.

Table 3 Pattern factor matrix

Label	Items	1	2	3
Prior Anxiety	I am afraid that humanoid robots will make us forget what it is like to be human	0.799	0.062	0.042
	I am afraid that humanoid robots will encourage less interaction between humans.	0.725	0.089	− 0.074
	I am concerned that robots would be a bad influence on children	0.726	0.001	− 0.085
	I don't know why, but humanoid robots scare me.	0.578	− 0.196	0.055
	I feel that if I depend on robots too much, something bad might happen	0.632	− 0.034	0.154
Prior Acceptance	I would want to boast that I have a robot in my home.	− 0.039	0.660	0.090
	I want to tame a robot according to my preferences.	0.289	0.651	− 0.043
	I feel the necessity for robots in my daily life.	− 0.101	0.517	0.109
	I feel easy around robots because I do not need to pay attention to robots as I do to humans.	− 0.098	0.565	0.018
	If a robot is introduced to my home, I think my children or grandchildren will be pleased.	− 0.129	0.545	− 0.111
Prior Anthropomorphism	I think robots will be able to perceive what I am going to do before I do it.	0.161	0.029	0.542
	I think robots will be more than a machine.	0.067	0.017	0.316
	I think robots will have sense of humour	− 0.130	0.049	0.544
	I am afraid that humanoid robots will make us forget what it is like to be human	0.163	0.005	0.579
	I am afraid that humanoid robots will encourage less interaction between humans.	− 0.150	− 0.041	0.792
% of variance explained		24.70	18.36	9.74
Cronbach alpha		0.85	0.73	0.70

Table 4 Between factors partial correlations. Significant results are presented in bold

		Prior Acceptance	Prior Anthropomorphism
Prior Anxiety	Pearson rho	**− 0.355**	**0.242**
	p value	**< 0.001**	**< 0.001**
Prior Acceptance	Pearson rho	x	**0.256**
	p value	x	**< 0.001**

Table 5 Partial correlation table attitudes factors*TRI. Significant results are presented in bold

		Optimism	Innovativeness	Negative
(F1) Prior Anxiety	Pearson rho	**− 0.131**	− 0.105	**0.334**
	p value	**0.036**	0.092	**< 0.001**
(F2) Prior Acceptance	Pearson rho	**0.255**	**0.280**	0.022
	p value	**< 0.001**	**< 0.001**	0.728
(F3) Prior Anthropomorphism	Pearson rho	− 0.050	0.021	**0.164**
	p value	0.421	0.735	**0.001**

6 Discussion

The objective of the second experiment was to identify specific factors that underlie attitudes towards robots, utilizing 48 carefully selected items from Experiment 1 through EFA. The outcomes of the EFA demonstrated a matrix of three factors, which incorporated 15 items, characterized by a harmonious blend of construct validity (52.80% of variance explained) and practicability (n = 15), as evidenced by a dependable Cronbach's α.

The first factor, referred to as "Prior Anxiety", consolidates negative items. Four of the five items convey an unfavorable outlook towards a future populated by robots. The fifth item, namely "I don't know why, but humanoid robots scare me.", is comparatively abstract. The factor, on the whole, gauges the degree to which individuals feel apprehensive about the implications of robots on humanity. In fact, the potential threat to mankind has been demonstrated to be a dependable forecaster of attitudes towards robots [87].

The second factor, referred to as "Prior Acceptance", gathers positive items. The majority of these items manifest optimistic attitudes and approval towards robots. These items draw a clear line of demarcation between robots and humans (e.g. "I find it effortless to be around robots as I do not have to pay as much attention to them as I do to humans.", "I aspire to train a robot in accordance with my own preferences."). This implies that the acceptance of robots is intertwined with the recognition of the distinctiveness between humans and robots.

The third factor, referred to as "Prior Anthropomorphism", collates items based on the MDRAS [22] and illustrates the perception of robots' (human-like) capabilities. These items entail endowing robots with social skills characteristic of humans (e.g. emotions, humor), as well as supra-human abilities (e.g. mind-reading, predicting actions) or highlighting the possibility that robots may be more than mere machines. The Prior Anthropomorphism factor displayed a positive correlation with the Anxiety factor, and a negative correlation with the Acceptance factor. This trend may signify a categorization threat. Specifically, a robot perceived as more human-like could diminish the sense of conceptual distance between a representation of a robot and a representation of *the self* [88], which can be seen as either devaluing (e.g. "I am like a robot") or threatening (e.g. "This robot could replace me") [89]. When faced with this categorization threat, individuals may experience anxiety, and as a result, demonstrate less acceptance towards robots.

Concerning the number of items that were excluded from the factorial analysis, it is intriguing to examine the semantics of the unselected items. Referring to the items listed in Table 2, we could potentially include an additional group of items. This group would comprise of items pertaining to preferences for the design and features of robots (e.g. I believe a robot should possess a humanoid physique, Robots are innovative and contemporary). The reason for this group not being a dependable factor is that it represents personal aesthetic preferences, which could potentially fluctuate in accordance with the three other factors.

To assess the external validity of the newly developed measure, we examined its scores in relation to the scores obtained from the Technology Readiness Index (TRI, [50]). Our expectation was that higher scores for technology readiness (TRI) would be positively correlated with more favorable attitudes towards robots (as per our scale). Conversely, we expected that lower levels of readiness for technology would be positively correlated with more unfavorable attitudes towards robots. Our expectations were confirmed by the correlation tables, which showed the following: firstly, a negative correlation between the Prior Anxiety dimension (ARM) and the Optimism dimension from the TRI scale, and a positive correlation between the Prior Anxiety dimension (ARM) and the aggregated value of Discomfort and Insecurity (i.e. Negative Attitudes) from the TRI scale. Secondly, the Prior Acceptance dimension (ARM) was positively correlated with the Optimism towards technology and Innovativeness dimensions from the TRI scale. Thirdly, the Prior Anthropomorphism dimension (ARM) was positively correlated with Negative Attitudes from the TRI scale. These findings are corroborated by the intra-factor correlation, which indicates that Prior Anxiety and Prior Anthropomorphism are positively correlated over a negative dimension, and as such, are linked to negative dimensions of technology readiness.

It is worth noting that the observed correlation indices were relatively modest, ranging from 0.13 to 0.32. The Technology Readiness Index's assumption that all technologies are dependent on the same attitudes (considering that optimism or anxiety towards using a toaster and a humanoid robot might differ significantly) might account for the low correlation values. Moreover, individuals differ in the degree to which they perceive robots as machines versus social agents [90]. The attitudes towards robots might also be highly variable amongst individuals due to a lack of direct experience with them, which could further contribute to the explanation of the low correlation indices.

6.1 Experiment 3

The aim of Experiment 3 was to conduct a confirmatory factor analysis (CFA) to verify the internal validity of the dimensions identified in Experiment 2 and to evaluate the external validity of the newly created scale. Gaskin's recommendations [91] and the literature on structural equation modeling [92, 93] were used to perform the CFA. To assess the external validity of the ARM, as in Experiment 2, the TRI was utilized as a comparison measure [50]. Furthermore, we investigated the relationship between the ARM dimensions and perceived robot anthropomorphism using the HRIES questionnaire [83] as additional measures of external validity, and examined the moderating effects of the ARM dimensions in an experimental paradigm.

Based on the premise that attitudes can predict the evaluation of robots [37], we devised a paradigm in which participants evaluated scenarios depicting a future populated by robots. Participants were prompted to contemplate robots on the human-machine continuum posited by Haslam [88]. As previously stated, Haslam's mechanistic dehumanization refers to regarding humans on a human-machine continuum. Assuming that humans can be perceived as more or less like machines (i.e. be dehumanized), a similar concept can be applied to artificial agents. Thus, artificial agents can also be perceived as more or less 'human' [37, 57, 58].

During the paradigm, participants were presented with a written text that aimed to prime them towards perceiving robots as either machines (i.e. *Dehumanized Robots* prime) or as entities closer to humans (i.e. *Humanized*

Robots prime). Subsequently, the participants rated their level of agreement with the text and assessed the degree to which they regarded the description as positive or negative. Finally, they completed the ARM.

We advance the following hypotheses: Firstly, in line with the findings of Müller and colleagues [87], we anticipate that participants in the Humanized Robots condition will perceive the text as more menacing and adopt more unfavorable attitudes, as compared to participants in the Dehumanized Robots condition. Secondly, we predict that the ARM's scores (as a surrogate measure of attitudes) will moderate the effects introduced by the textual prime manipulation. Specifically, we expect that in the Humanized Robots condition, participants with higher Prior Anxiety scores (ARM) will appraise the text more negatively, whereas participants with higher Prior Acceptance scores (ARM) will provide more positive evaluations [30]. With regards to the factor Prior Anthropomorphism, we posit that participants with higher Prior Anthropomorphism scores (ARM) will concur more with the Humanized (as compared to Dehumanized) Robots text, as the depiction will better align with their prior expectations.

Taking into account the extensive evidence that attitudes towards agents affect attributions towards these agents (in both humans [17, 94] and robots [95]), we also examined the connection between the ARM dimensions and perceived robot anthropomorphism. Prior research has demonstrated that individuals with favorable attitudes towards robots are more inclined to associate them with human-like traits or capabilities [53, 83]. To assess the relationship between the ARM and perceived robot anthropomorphism, we utilized the Human-Robot Interaction Evaluation Scale (HRIES) as a metric of anthropomorphism [83]. The HRIES consists of four dimensions: Sociability (pertaining to the attribution of qualities associated with a positive interaction, such as "warmth"), Agency (pertaining to the attribution of intentionality, e.g. "intentional"), Animacy (pertaining to the liveliness of the agent, e.g. "alive"), and Disturbance (pertaining to the discomfort linked to a robot, e.g. "uncanny"). The HRIES measures the anthropomorphic attributions towards a particular artificial agent.

Expanding upon prior literature [53, 83], we posited that ARM attitudes, as a precursor for assessing robots, would forecast the ascription of anthropomorphic traits. Specifically, we predicted that the Prior Anxiety dimension of the ARM will exhibit a positive correlation with the Disturbance dimension of the HRIES [30, 95]. Conversely, we predicted that the Prior Acceptability dimension of the ARM will exhibit a positive correlation with the ascription of Sociability, Agency and Animacy within the HRIES's dimensions [53]. A comparable association was expected for the Prior Anthropomorphism dimension. Namely, as it measures an ascription of human-like abilities (e.g. humor, emotion reading), we anticipated that it will positively forecast HRIES's Sociability, Agency and Animacy attributions.

6.2 Method

One hundred and seventy-one participants (62 males and 109 females, $\mu_{age} = 35.21$, $SD = 12.76$) recruited via Prolific took part in Experiment 3. The sample size was determined following the recommendations in factor analyses literature [96]. Specifically, based on the number of items ($q = 15$), at least 10 observations are recommended for CFA [96], resulting in a minimum of 150 required participants in the current experiment.

As in Experiment 2, participants first completed the short version of the TRI [50] with the Optimism ($\alpha = 0.70$), Innovativeness ($\alpha = 0.81$), Discomfort ($\alpha = 0.65$), and Insecurity ($\alpha = 0.64$) dimensions. As in experiment 2, we aggregated the Discomfort and Insecurity dimensions into a single factor: Negative Attitudes. As the aggregated alpha ($\alpha = 0.65$) did not reach the recommended threshold (i.e. $\alpha = 0.70$), we consider the results regarding this dimension with caution.

Second, participants completed the 15 items of our newly created ARM scale with the Prior Anxiety ($\alpha = 0.85$), Prior Acceptance ($\alpha = 0.70$), and Prior Anthropomorphism ($\alpha = 0.78$) dimensions. In order to maintain consistency, items displaying the label "humanoid robots" were homogenized to "robots".

Third, participants were randomly assigned to one of the two experimental conditions (*Dehumanized Robots* or *Humanized Robots*). The humanization prime (*Humanized Robots* condition) was designed to reduce the distinction between the (concepts of) humans and robots, while the dehumanization prime (*Dehumanized Robots* condition) was designed to increase the distinction between the (concepts of) humans and robots.

- Humanized robots textual prime: In the next decade, it is likely that robots will develop some form of consciousness. They will be able to make their own decisions similar to humans and will behave like humans. Robots will populate our world and will probably become a new form of living beings. Once human consciousness is computerized, the difference between robots and humans is likely to thin or, eventually, disappear.
- Dehumanized robots textual prime: In the next decade, it is unlikely that robots will develop some form of consciousness. They will not be able to make their own decisions like humans do, or behave like humans. Robots will populate our world in the form of tools for human activities. The complexity of human consciousness is

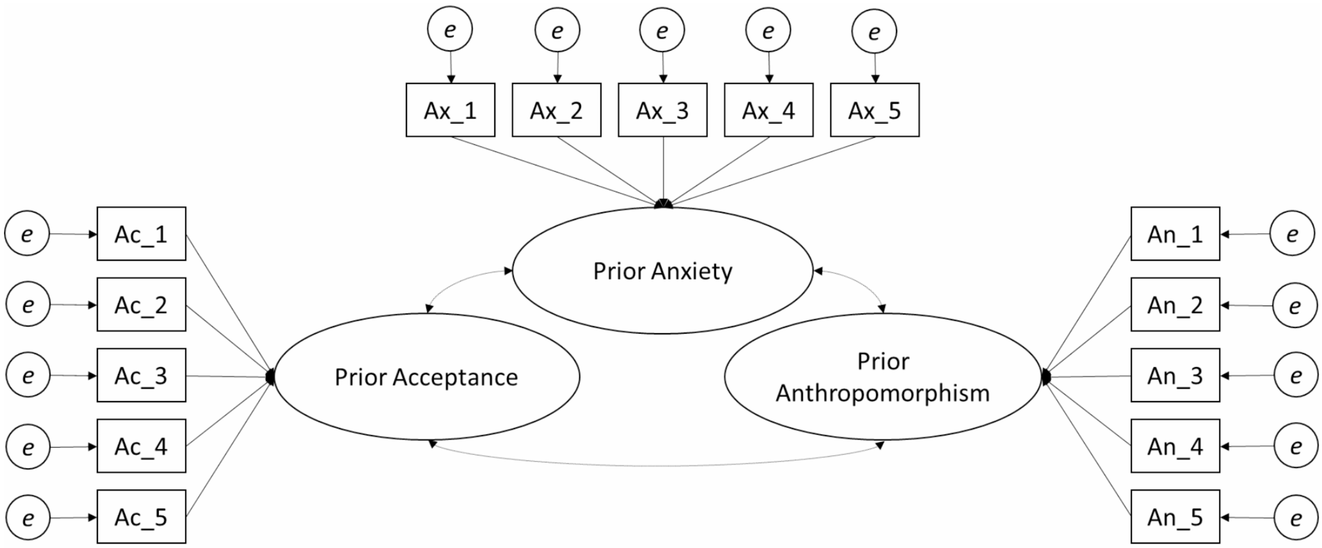

Fig. 2 Confirmatory factor analysis model

Table 6 Confirmatory model fit indices. χ2/df the ratio of chi square to degree of freedom; 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
χ2/df	≤3.00	1.69
CFI	≥0.90	0.92
TLI	≥0.90	0.91
RMSEA	≤0.08	0.06
CI90%		[0.05; 0.08]
SRMR	≤0.09	0.09

nearly impossible to be computerized, therefore robots will never become equal to humans.

After reading the textual prime, as a manipulation check, participants evaluated, on a scale from 1 ("totally disagree") to 7 ("totally agree"), the extent to which they agreed with the text.

Fourth, participants were presented with the iCub robot. They evaluated the robot's anthropomorphic characteristics using the Human-Robot Interaction Evaluation Scale (HRIES) [83]. The scale consists of four sub-dimensions including Sociability (e.g., Warm, α = 0.83), Agency (e.g., Self-reliance, α = 0.77), Animation (e.g., Alive, α = 0.70), and Disturbance (e.g., Creepy, α = 0.80). For each item, participants rated whether they agreed or disagreed (on a scale from 1 to 7) with attribution of related characteristics to the presented robot.

Finally, the participants answered demographic questions relating to age, gender, and educational level.

Table 7 Composite reliability for each factor

Factor	Composite Reliability	Average Variance Extracted
Prior Anxiety	0.85	0.73
Prior Acceptance	0.70	0.56
Prior Anthropomorphism	0.79	0.65

7 Results

7.1 Confirmatory Factor Analysis

To test the reliability of the factors identified in Experiment 1, we conducted a CFA, with a structural model (Fig. 2) [92, 97, 98], using AMOS plugin in SPSS. We used a variance-covariance matrix with a maximum likelihood (ML) estimation [99]. ML estimation has proved to be highly reliable [100].

The model-fit indices revealed a chi square (χ2) value equal to 141.90 ($df = 84$, $p < .001$). Table 6 shows the model-fit indices [93, 101] along with the recommended thresholds [97].

We evaluated the composite reliability (internal consistency of the scale's items) defined as the total amount of the true score variance relative to the total scale score variance (the recommended reliability threshold was 0.70 [102]) and averaged variance extracted (the positive square root of the average variance extracted for each of the latent variables should be higher than the highest correlation with any other latent variable) [103]. (Table 7). Both criterion reached their respective acceptability thresholds.

Table 8 presents the non-standardized estimates for each item associated with its common factor (all $p_s < 0.001$).

Table 8 CFA standardized estimates

Item		Factor	b	*t* value	*p* value
ZAx_1	<---	Prior Anxiety	0.760	10.96	< 0.001
ZAx_2	<---	Prior Anxiety	0.641	7.98	< 0.001
ZAx_3	<---	Prior Anxiety	0.694	8.66	< 0.001
ZAx_4	<---	Prior Anxiety	0.784	9.79	< 0.001
ZAx_5	<---	Prior Anxiety	0.771	9.64	< 0.001
ZAn_1	<---	Prior Anthropomorphism	0.742	10.44	< 0.001
ZAn_2	<---	Prior Anthropomorphism	0.512	7.36	< 0.001
ZAn_3	<---	Prior Anthropomorphism	0.394	5.78	< 0.001
ZAn_4	<---	Prior Anthropomorphism	0.642	7.29	< 0.001
ZAn_5	<---	Prior Anthropomorphism	0.428	6.50	< 0.001
ZAc_1	<---	Prior Acceptance	0.638	7.36	< 0.001
ZAc_2	<---	Prior Acceptance	0.521	5.17	< 0.001
ZAc_3	<---	Prior Acceptance	0.695	4.12	< 0.001
ZAc_4	<---	Prior Acceptance	0.597	5.90	< 0.001
ZAc_5	<---	Prior Acceptance	0.760	4.43	< 0.001

Table 9 Between factors partial correlation table. Significant results are presented in bold

		Prior Acceptance	Prior Anthropomorphism
Prior Anxiety	Pearson rho	**− 0.225**	**0.317**
	p value	**0.003**	**0.000**
Prior Acceptance	Pearson rho	x	**0.212**
	p value	x	**0.005**

Table 10 Partial correlation table attitudes factors*TRI. Significant results are presented in bold

		Optimism	Innovativeness	Negative
Prior Anxiety	Pearson rho	− 0.028	− 0.100	**0.245**
	p value	0.721	0.200	**0.001**
Prior Acceptance	Pearson rho	**0.311**	**0.266**	− 0.130
	p value	**< 0.001**	**0.001**	0.093
Prior Anthropomorphism	Pearson rho	**0.170**	− 0.025	− 0.056
	p value	**0.028**	0.743	0.471

We introduced the three factors into a partial correlation matrix to control for covariance (Table 9). The results showed that Prior Anxiety was negatively correlated with Prior Acceptance and positively correlated with Prior Anthropomorphism factors. Prior Anthropomorphism was also positively correlated to Prior Acceptance.

Table 11 Partial correlation table attitudes factors*HRIES. Significant results are presented in bold

		Sociability	Animacy	Agency	Disturbance
Prior Anxiety	Pearson rho	− 0.128	− 0.067	0.084	**0.441**
	p value	0.098	0.390	0.278	**< 0.001**
Prior Acceptance	Pearson rho	**0.455**	**0.259**	**0.360**	− 0.052
	p value	**< 0.001**	**0.001**	**< 0.001**	0.507
Prior Anthropomorphism	Pearson rho	**0.215**	**0.318**	**0.389**	0.129
	p value	**0.005**	**< 0.001**	**< 0.001**	0.165

7.2 External Validity

7.3 Technology Readiness Index (TRI)

As in Experiment 2, to test the external validity of the current measure, we correlated each of the ARM's factors with the three TRI dimensions (Optimism, Innovativeness, Negative Attitudes) controlling for age, gender and educational level (Table 10). Our results confirmed the results of Experiment 2 with the exception of Prior Anthropomorphism dimension which did not correlated with the Innovativeness (TRI) dimension.

A post-hoc analyses revealed that the experimental group assignment (*Dehumanized vs. Humanized Robots*) interacted with the correlation estimates on Prior Anxiety dimension. While there was no correlation in the *Dehumanized* group, $r = -.19$, $p = .084$, in the *Humanized* group, the correlation with Prior Anxiety was significant, $r = -.25$, $p = .023$.

7.4 Human Robot Interaction Evaluation Scale

The partial correlation matrix between the factors of the newly created scale and the HRIES dimensions showed a positive correlation between Prior Anxiety (ARM) and the attribution of Disturbance traits (HRIES). Prior Acceptance and Prior Anthropomorphism (ARM) were also positively correlated with each of the HRIES dimensions (Table 11).

7.5 Dehumanized vs. Humanized Robot

In order to examine the moderating impacts of the ARM dimensions on the evaluations of robots in relation to the experimental manipulation (Dehumanized vs. Humanized

Robots), we conducted moderation analyses for each of the ARM dimensions. We incorporated the experimental condition as an independent variable, the evaluations as the dependent variable, and the ARM dimensions as moderators. Additionally, we introduced the participants' age, gender, and educational level, as well as their levels of agreement with the textual prime, as covariates (Fig. 3).

Participants in the *Humanized Robots* condition evaluated the text more negatively (compared to the participants in the *Dehumanized Robots* condition), $F(1, 170) = 40.44$, $p < .001$, $CI_{95\%}$ [-2.09, -1.10].

Prior Anxiety. Moderation analyzes revealed that Prior Anxiety was a significant moderator of the observed effects $B = -0.51$, $t(169) = -3.53$, $p = .005$, $CI_{95\%}$ [-0.80, −0.22]. While there was no significant effect of Prior Anxiety in the *Dehumanized Robots* condition, $B = -0.08$, $t(169) = -0.76$, $p = .447$, $CI_{95\%}$ [-0.28, 0.13], in the *Humanized Robots* condition, the more participants declared prior anxiety toward robots, the less they rated the text positively, $B = -0.59$, $t(169) = -5.87$, $p < .001$, $CI_{95\%}$ [-0.79, −0.39].

Prior Acceptance. The moderation was also significant for Prior Acceptance, $B = 0.57$, $t(169) = 2.75$, $p = .007$, $CI_{95\%}$ [0.16, 0.97]. While there was no moderation effect in the *Dehumanized Robots* condition, $B = -0.18$, $t(169) = 2.64$, $p = .009$, $CI_{95\%}$ [0.10, 0.68], in the *Humanized Robots* condition, participants scoring higher on Prior Acceptance considered the humanization of robots more positively, $B = 0.39$, $t(169) = 2.64$, $p = .009$, $CI_{95\%}$ [0.10, 0.68].

Prior Anthropomorphism. Participants scoring higher on Prior Anthropomorphism reported stronger beliefs in *Humanized Robots* prime, $r = .35$, $p = .001$, and less agreement with the *Dehumanized Robots* textual prime, $r = -.31$, $p = .004$. However, the moderation analysis failed to reach significance, $B = -0.06$, $t(169) = -0.31$, $p = .754$, $CI_{95\%}$ [-0.46, 0.33].

8 Discussion

The aim of Experiment 3 was to verify the psychometric properties of the recently formulated ARM measure by carrying out a CFA and a series of external validations. Regarding the internal consistency, CFA demonstrated dependable fit indices with an adequate composite reliability and average variance explained. All items were found to load onto their respective factors. Hence, the final matrices comprised 15 items (see Table 12).

In relation to external validity, we initially correlated the ARM dimensions with the TRI dimensions. The findings were mostly consistent with our hypotheses. Prior Anxiety (ARM) exhibited a positive correlation with Negative Attitudes towards technology (TRI). Prior Acceptance (ARM) displayed a positive correlation with both Optimism and Innovativeness (TRI). Prior Anthropomorphism was positively associated with Optimism (TRI). Additionally, the results indicated that the concept of robots possessing human capabilities can elicit mixed emotions among participants, depending on their perceptions of robots [6]: while some may view it as a reason for optimism, others may view it as a source of insecurity.

Regarding the connection between the ARM and the perceived anthropomorphism of robots, measured through HRIES, the findings were in line with our expectations. Prior Anxiety (ARM) demonstrated a positive correlation with the attribution of Disturbance traits (HRIES). Prior Acceptance and Humanization (ARM) exhibited positive correlations with favorable attributions (Sociability, Agency, and Animacy).

Ultimately, we assessed the ARM dimensions for moderating effects in an experimental paradigm. Two ARM dimensions played a vital role in our experimental manipulation. Consistent with our hypotheses, after reading the text outlining the decrease of human-robot distinction in

Fig. 3 Moderation model

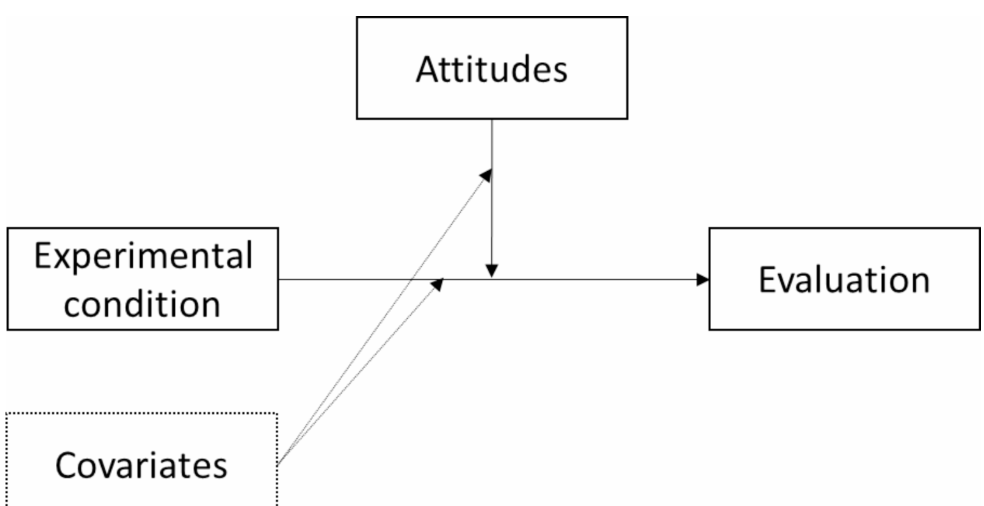

Table 12 Final version of the ARM with the four sub-dimensions

Label	Items
Prior Anxiety	I am afraid that robots will make us forget what it is like to be human
	I am afraid that robots will encourage less interaction between humans.
	I am concerned that robots would be a bad influence on children
	I don't know why, but robots scare me.
	I feel that if I depend on robots too much, something bad might happen
Prior Acceptance	I would want to boast that I have a robot in my home.
	I want to tame a robot according to my preferences.
	I feel the necessity for robots in my daily life.
	I feel easy around robots because I do not need to pay attention to robots as I do to humans.
	If a robot is introduced to my home, I think my children or grandchildren will be pleased.
Prior Anthropomorphism	I think robots will be able to perceive what I am going to do before I do it.
	I think robots will be more than a machine.
	I think robots will have sense of humour
	I am afraid that robots will make us forget what it is like to be human
	I am afraid that robots will encourage less interaction between humans.

the future (Humanized Robots condition), participants evaluated the situation more negatively (compared to the text emphasizing an increase in human-robot distinction, i.e. Dehumanized Robots group). The moderation analyses indicated that Prior Anxiety towards robots (ARM) amplified this effect, and conversely, higher Prior Acceptance of robots (ARM) weakened it. Prior Anthropomorphism was related to stronger belief in the Humanized Robots description and a lower belief in the Dehumanized Robots description. These results, aligned with the distinctiveness threat to human identity [87], indicate that this threat is moderated by prior attitudes towards robots. Specifically, individuals with higher prior levels of acceptance towards robots are more likely to accept a decrease in human-robot distinction, whereas individuals with higher prior levels of anxiety towards robots are less likely to accept it. Overall, the findings of the experiment underscore the moderating performance of ARM and collectively contribute to the construct reliability evidence for the newly developed scale.

8.1 General Discussion

Attitudes are an integral aspect of human behavior [104]. With the increasing prevalence of artificial intelligence in our daily lives, it is imperative to accurately predict users' attitudes towards these novel artificial agents. Despite the existence of various measures to gauge attitudes towards robots, they are plagued by poor psychometric performance [28]. In this report, we have devised a new scale of attitudes towards robots (ARM) by consolidating previous questionnaires [19–24, 27]. Our scale addresses the methodological gaps identified by Krägeloh and colleagues [28] by adhering to the recommended questionnaire development methodology [64, 65].

Through three studies, we carefully selected the most reliable items from 111 items that were previously used in scales [19–24, 27]. We then identified common dimensions that underlie attitudes towards robots, refined them, and assessed their internal, external, and construct validity. To ensure the external validity of the newly created measure, we also correlated the ARM scores with measures of attitudes towards technology (TRI [50]) and the attribution of anthropomorphic characteristics (HRIES [83]). Finally, we examined the moderating role of ARM's attitudes on the evaluation of futuristic robot scenarios by manipulating the human-robot distinction [87].

The Attitudes towards Robot Measure (ARM) was thus established and standardized with 15 items distributed across four dimensions: Prior Anxiety, Prior Acceptance, and Prior Anthropomorphism. These dimensions illustrate both negative (Anxiety) and positive (Acceptability) attitudes [19, 38, 105], as well as expectations regarding robots' capabilities and their human-like characteristics [6]. In the current study, these three dimensions were found to be the principal components of attitudes towards robots.

It is interesting to note that regularities can be extracted from the two experiments. Firstly, with regard to technology readiness, positive attitudes towards technology were found to be related to Acceptance of robots and Anthropomorphism, whereas negative attitudes towards technology were related to Anxiety. These results confirm that robots are evaluated based on their technological nature to a certain extent [106]. Therefore, attitudes towards robots are not solely determined by their representation but also by a general view of technology as positive or negative. Additionally, results from the HRIES indicate that individuals also develop their attitudes with a social perspective. In our experiments, attitudes were related to social categorization with the attribution of social competences or agency (positively related to Acceptance and Anthropomorphism) and disturbance (positively related to Anxiety) to robots. It is worth noting that a prior anthropomorphic view of robots (as imaginative anthropomorphism, [54]) was a reliable predictor of social inferences but not disturbance. This lack of significant results on disturbance needs to be considered in light of Fiske, Cuddy, and Glick theory [107]. When Prior Anxiety towards robots appears, it must be considered with sufficient competences and abilities so that it can actually be perceived as a "threat" resulting in disturbance. Considering the correlation between Prior Anthropomorphism and Anxiety, it can be hypothesized that the higher the Prior Anthropomorphism, the higher the Prior Anxiety as a mediator, and therefore the higher the disturbance (HRIES) should be. We conducted a post-hoc mediation analysis to validate this hypothesis (indirect effect: $b = -0.06$, $z = 2.19$, $p = .028$, $CI^{95\%}$ [-0.12, −0.01], total effect: $b = 0.01$, $z = 0.10$, $p = .918$, $CI^{95\%}$ [-0.15, 0.17]).

Therefore, while in the current report we present 3 separate factors, a hierarchical relationship between the dimensions cannot be precluded. For example, it is possible that Anxiety might affect the evaluation of Acceptance. For example, while anxious and non-anxious individuals could share the idea that robots will be imbued with anthropomorphic characteristics in the future, this prospect could be perceived more negatively for anxious individuals than for non-anxious individuals. As a consequence, the former group could show less acceptance of robots. The psychological hierarchy among the dimensions shall thus be addressed in future research. We conducted an exploratory hierarchical clustering analysis on study 3 data including the 3 factors. Results showed a first cluster including Prior Acceptance and Prior Anthropomorphism, further related to the Prior Anxiety as a negative cluster. According to this result, Anthropomorphism would be, at first, a positive attribution close to Acceptance. Based on this result we investigated different relationship models between the three factors. The model presenting the best fit indices was the model including the Anthropomorphism as first layer predicting both Acceptance (positive effect, $b = 0.22$, $t(170) = 2.82$, $p = .005$, $CI^{95\%}$ [0.06, 0.34]) and Anxiety (positive effect, $b = 0.28$, $t(170) = 3.83$, $p < .001$, $CI^{95\%}$ [0.17, 0.52]). Also, Anxiety moderated the relationship between Anthropomorphism and Acceptance, $b = -0.06$, $CI^{95\%}$ [-0.12, −0.01]) while Acceptance did not moderated Anxiety ($b = -0.04$, $CI^{95\%}$ [-0.10, 0.01]). Therefore, Anthropomorphism seems a prior on which are developed Acceptance and Anxiety feelings. This result argue that people form attitudes toward robots based on an (more or less) anthropomorphic representation of robots that may trigger positive (e.g. Acceptance) or negative (e.g. Anxiety) affects. Interestingly, based on the exploratory analysis, these two effects may exist in parallel arguing for an ambiguity regarding attitudes toward robots, and ambiguity that has been previously discussed [6, 108] and may now be measured with the ARM.

"As previously noted, attitudes toward robots are primarily driven by expectations rather than direct experiences, rendering them somewhat malleable [37]. It is important to acknowledge that individuals tend to seek out information that confirms their pre-existing beliefs [109, 110], and that attitudes towards robots might be influenced by various factors, including social relationships, general objectives, and exceptional events such as socio-political, economic, and environmental circumstances [111]. All of these factors contribute to the formation of attitudes towards robots. Moreover, representations of robots are known to evolve over time as a result of exposure to them [112]. For instance, involving individuals in the development of robots can lead to increased positive attitudes and decreased anxiety towards them [113]. Consistent with these findings, Nomura and colleagues suggest that people may hold negative attitudes towards robots when they lack familiarity with them, but knowledge about robots can positively shift and alter their attitudes [114]. The extent to which actual interactions with robots or information can change individuals' attitudes towards robots in the long term remains an open question."

When considering the relationship between attitudes and behaviors in HRI, it is essential to take into account the three factors of the ARM model. Firstly, anxiety has been found to hinder the willingness to interact. Thus, it is imperative to assess prior anxiety before introducing robots, particularly in social environments where they may be perceived as an additional stressor. Secondly, acceptance is a positive influencer of willingness to interact [115]. This factor also includes items related to incorporating the robot into one's own social circle (e.g. family), which can serve as an indicator of the acceptance of the robot as a social entity in its own right. Thirdly, prior anthropomorphism can be viewed as a marker of the type of interaction (e.g. mechanistic versus humanistic) that one may engage in with a robot. This point is intriguing to consider regarding the differential effects on social cognition processes when regarding a robot either as a machine or a human [116–118]. Lastly, it is important to note that although the three factors are interrelated, they exist in parallel, meaning that individuals may hold mixed attitudes towards robots. Therefore, depending on the context, we may expect different attitudes to be expressed. This raises several questions about the relationship between attitudes, context, and behaviors in the case of HRI, which require further investigation given the wide range of attitudes and their potential malleability.

Lastly, it is worth noting that during the publication process of this paper, Koverola and colleagues [119] developed a parallel scale called GATORS. This scale focuses on evaluating attitudes at both individual and societal levels and provides an interesting orthogonal factorization. The ARM and GATORS do not approach attitudes with the same perspectives; while the ARM aims to characterize attitudinal priors, the GATORS provides information about attitudes regarding the broader usage and development of robots. As a result, the factors of the GATORS demonstrate more collinearity than those of the ARM. Further research should investigate the predictive capabilities of each scale and their complementary explanatory power.

9 Conclusion

In the coming decades, it is highly likely that HRIs will increase on a global scale. As attitudes towards robots will be a crucial factor in predicting the success of such interactions, a reliable tool for assessing attitudes towards humanoid robots is necessary. Following psychometric standards, we present the development and validation of a new measure of attitudes towards robots (ARM). The ARM consolidates items from previously available questionnaires on the subject. The scale comprises three factors: prior anxiety, acceptance, and anthropomorphism, and is characterized by a good balance of construct validity and the practicality of the number of items (n = 15). This new instrument can be utilized to evaluate attitudes towards robots.

Data Availability Data can be accessed at https://osf.io/4aduw/.

Declarations

Conflict of interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethics Statement This study was carried out in accordance with the provisions of the World Medical Association Declaration of Helsinki. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

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