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# The body images of social robots\*

Bing Li<sup>1</sup>, Oumayma Ajjaji<sup>1</sup>, Robin Gigandet<sup>1</sup> and Tatjana Nazir<sup>1</sup>

**Abstract**—The rapid development of social robots has sparked a challenge for both robotics and cognitive sciences to comprehend how humans perceive the appearance of robots. This understanding is a crucial prerequisite for achieving successful human-robot symbiosis. To uncover people’s perceptions and attitudes towards robots, we analyzed image-associated words generated spontaneously by humans for 30 robots developed in the past decades. These words delineated a *body image* for each of the robots. We then used word affective scales and embedding vectors to provide evidence for links between human perception and the body images. Our findings revealed that the valence and dominance of the body images reflected human attitudes toward the general concept of robots. The study further demonstrated that the user-base and usage of robots significantly influenced people’s impressions of individual robots. Moreover, we investigated the psychological and cultural implications of the body images by examining semantic distances between the robots and a human-related word, as well as gender- and age-distinguished words. This analysis revealed a relationship between the semantic distances to the word “person” and the robots’ affects, as well as gender and age stereotypes towards the robots. Our study demonstrated that using words to build body images for robots is an effective approach to understanding which features are appreciated by people and what influences their feelings towards robots.

## I. INTRODUCTION

Body image refers to the subjective perception and evaluation of one’s own physical appearance, encompassing attitudes, feelings and cultural implications. Given the fast growth of robots in people’s life, revealing what is implied in the body images of robots will help us improve the relationship between us and our artificial companions. The present study aims to understand how humans perceive robots and how they form semantic representations of the robots from purely visual characteristics. The term “body image” will be used to refer to the semantic understanding a person derives from viewing (images of) robots.

Neuroscientific research has shown that visual input to the brain is transformed into semantic representations through a default path [1]. Visual traits such as strokes, shapes, and colors are processed in the occipital lobe and then transmitted to the frontal and temporal lobes through pathways for semantic interpretation of the object [2]. Importantly, significant traits such as faces and word forms are processed in dedicated regions close to occipital regions [3], [4], before

other semantic information is processed in the temporal lobe [5]–[7]. Recently, a third pathway has been proposed that is specialized in processing social cues [8]. These pieces of evidence suggest that the human brain possesses a default system [1] that interprets visual inputs and generates semantic outputs. Therefore, the body image of a robot encompasses not only the visual appearance of the robot but also its semantic meaning and social significance.

Studies in semantics provided models about how concepts are organized in the brain’s semantic system. In psycholinguistics, a commonly used model is the word embedding model [9]. This neural network model extract the likelihood of words appearing next to each other in large, naturally occurring texts typically found on the internet, and represents words using vectors. Research has shown that this model accurately reflects real-world semantic information [10]. The spontaneous word association method can effectively uncover individuals’ underlying perceptions and attitudes towards robots by analyzing the words they associate with them [13]. Therefore, rather than focusing on the visual appearance of robots, which can often be difficult to quantify and interpret, incorporating a person’s understanding of a robot’s appearance into such a semantic framework could be more transparent and easier to implement.

With the goal of understanding human’s mental representation of social robots, we propose to examine the characteristic features of robots from a semantic perspective. A free word-association task will be used to collect basic impressions about various robots and to model the data within a semantic space using word vectors. We will also quantify the affective dimensions of the words using “valence”, “arousal” and “dominance” measurements from an affective lexicon [11]. Moreover, we will determine how the word-vector that characterize a given robot relate to the word “person” within the semantic space, to assess how closely participants associate the robot with the human environment. Finally, we will investigate potential human stereotypes using two sets of opposing concepts (gender and age) to analyze the positioning of social robots on these semantic dimensions.

## II. METHODS

### A. The robot stimuli and human participants

We selected 30 robots from the robots available on the market or as prototypes in the past decades. To ensure a broad range of diverse features, the robots chosen for this study exhibit a wide variety of characteristics, including the presence or absence of a face, legs, arms, and resemblance to typical animal- or human-shapes. The robots included into the study are: Buddy, Eilik, Musio, Pico, Sima,

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TABLE I

THE ROBOT ATTITUDE QUESTIONNAIRE (RAQ) USED TO MEASURE PARTICIPANTS' ATTITUDES TOWARDS THE GENERAL CONCEPT OF ROBOTS. IT PRECEDED THE FREE ASSOCIATION TASK.

INSTRUCTION	Please select the option that best describes your attitude at the moment:
STATEMENTS	I want a robot to assist me ... (1) ... at home (2) ... at school (3) ... in dangerous locations (4) ... in factories (5) ... in hospitals (6) ... in hotels (7) ... in museums (8) ... in offices (9) ... in police stations (10) ... in public transportations (11) ... in shopping centers (12) ... in sports facilities
RESPONSES	<input type="checkbox"/> Strongly disagree <input type="checkbox"/> Disagree <input type="checkbox"/> Neither agree or disagree <input type="checkbox"/> Agree <input type="checkbox"/> Strongly agree

Aibo, Ameca, Aquanaut1, Asimo, Astro, Atlas, Emiew, Hexa, Hitchbot, iCub, Jibo, Lovot, Minicheetah, Moxie, Nao, Neubie, Nicobo, Optimus, Parky, Pepper, Pyxel, Sawyer, Spotmini, Talos, Vector.

It is pertinent to note that the concept of a robot is ambiguous, and it can be challenging to determine which entities should be included within this classification. A common

TABLE II

THE FREQUENCY OF THE TOP 30 WORDS IN THE FREE ASSOCIATION TASK, BASED ON ALL THE 30 PARTICIPANTS AND 30 ROBOTS.

	Word	Frequency
1	toy	42
2	cute	39
3	friendly	33
4	small	30
5	robot	29
6	helpful	28
7	scary	25
8	future	23
9	dog	22
10	creepy	17
11	fun	16
12	human	16
13	technology	16
14	child	14
15	cool	14
16	weird	14
17	animal	12
18	simple	12
19	happy	11
20	smart	11
21	strong	11
22	artificial intelligence	10
23	assistant	10
24	automatic	10
25	color	10
26	helper	10
27	modern	10
28	useful	10
29	wheels	10
30	automated	9

example is quadrotor aircraft, or drones. While some may consider drones as robots, as evidenced by their inclusion in the IEEE Robotics & Automation Society's robots list<sup>1</sup>, others may perceive them simply as aircraft. However, the present study focuses on investigating the robot body image as a basis for human-robot interaction, a goal that does not align with the typical applications of drones. Therefore, drones were excluded from the current investigation.

The experiment was conducted on the Prolific platform<sup>2</sup> and built with psychJS [12]. Before publishing the experiment task, we set pre-screening filters to only include native English speaker between 18 and 30 year old to maintain the homogeneity of the age span, within which people are very likely to grow up with internet, and more open to new technologies.

Before the tasks, participants were informed that they can quit the task at any moment during the task and will be compensated for the time spent on the task<sup>3</sup>. The task averagely took 14 minutes per participant. Compensation was of about €7.15/hour. Thirty participants were recruited into the experiment.

### B. Experimental procedure

The experiment consisted of two distinct sessions aimed at 1) measuring attitudes towards robots and 2) constructing their corresponding body images.

1) *The robot attitude scale*: To assess attitudes, we designed a questionnaire, the Robot Attitude Questionnaire (RAQ). The RAQ was adapted from a study by Lee and Sabanović [15] that explored cross-cultural differences in attitudes towards robots. The questionnaire comprised statements pertaining to the willingness of participants to seek assistance from robots in various situations and used a Likert scale rating (see Tab. I). Participants were required to select the option that best represented their attitude on a 5-point Likert scale ranging from 0 - "Strongly disagree" to 4 - "Strongly agree". To calculate the overall attitude score of a participant, scores from all the statements were averaged. Participants completed the Robot Attitude Questionnaire (RAQ) prior to engaging in the free association task. Therefore, the term "robot" in the RAQ did not refer to any specific robot model but instead represented the general concept of robots.

2) *Free association*: To construct the robot's body images we used a free association task [13], [14]. Following completion of the questionnaire, participants were instructed to provide 6 words that came to their minds in response to each of 10 sequentially presented images. The images were presented at the top of the screen, followed by 6 text boxes for each image. The participants were required to enter the words in a sequential manner, from the 1st to the 6th text box, and click on the "Finished" button to proceed to the next image. To expedite the process of moving to the next

<sup>1</sup><https://robots.ieee.org/robots/> (April 18, 2023).

<sup>2</sup><https://app.prolific.co>

<sup>3</sup>The study was approved by the ethics committee at the University of Lille with the reference number 2023-663-S113.

word after entering a word, participants used the “Enter” key. For each image, participants were required to enter all 6 words, and skipping any text box was not permitted. The “Auto fill-in” functionality of the psychJS program utilized in the study was disabled.

To mitigate the potential for intra-correlation among participants, whereby individuals might demonstrate similar behaviors across the observed robots, a randomized robot selection procedure was implemented. The randomization approach is detailed in [16]. As a result of this method, each participant viewed a distinct subset of 10 robots.

Tab. II displays the top 30 most commonly reported words.

### C. Word vectors and affect measurements

To represent words as vectors, the Word2vec model pre-trained on Wikipedia news by FastText was utilized<sup>4</sup>. The resulting vectors possessed 300 dimensions. Given that a robot is associated with multiple words, the vectors for the different words were averaged to create a single 300-dimension vector for each robot, as illustrated in Fig. 2. To quantify the affective dimensions of words, the valence, arousal, and dominance (VAD) measurements from Mohammad’s [11] affective lexicon were used. This lexicon contains VAD ratings for 20,000 English words based on best-worst scaling [11], [16].

After data collection, the responses were pre-processed. This involved converting plural words into their singular forms and converting capitalized words to lowercase. For compound words and phrases, the most representative word was primarily extracted. For example, “canfly” was replaced with “fly” and “car-like” was replaced with “car”. However, in cases where representativeness was difficult to determine, such as “artificial intelligence”, the entire compound was omitted.

Due to the limited size of the VAD lexicon, some adjectives were not present in the VAD lexicon, but their synonyms were. For example, “gangly” was not in the lexicon, but “awkward” was present and used instead. In such cases, synonyms were obtained from the Merriam-Webster thesaurus<sup>5</sup>. After pre-processing, the VAD lexicon covered 92.33% of the responses. In the lexicon, the values of the affective dimensions ranged between 0 to 1, with a higher value indicating a higher affective rating.

## III. RESULTS

### A. Word affects predicts subjective attitude

At participant-level, we investigated whether the general attitude towards robots can be predicted by affective measures of the associated words. Three linear mixed-effect (LME) models were built with attitude scores as the dependent variable and affective measures as the only fixed-effect independent variable respectively. Robots with random intercepts were included as the maximized random-effect structure.

<sup>4</sup><https://fasttext.cc/docs/en/english-vectors.html>

<sup>5</sup><https://www.merriam-webster.com/thesaurus/>

The results showed that valence is a strong predictor for attitude (likelihood ratio test, LRT  $\chi^2 = 15.577, p < .000$ ), and dominance is a strong predictor for attitude (LRT  $\chi^2 = 19.529, p < .000$ ). However, arousal did not predict attitude (LRT  $\chi^2 = 2.101, p = .146$ ). Figure 1 illustrates the relationships between attitudes and affective measures. The values of the affective measures for each of the three features (valence, dominance, arousal) were averaged across words for each participant. Each dot in the figure represents one participant. The results show that the semantic associations of a robot’s body image are reflective of the attitude of the observer.

### B. The graph of body images

Robot classification methods generally vary and can include shape, function, and usage. However, the extent to which these features influence human perception of robots has not been extensively studied. Here, we created a graph of the 30 robots based on the average word vectors associated with each of the robots. We then used pair-wise cosine similarity to connect each robot to its three most similar robots (as shown in Fig. 2 and Fig. 3D). The graph identified the robot types commonly known as humanoids, robot assistants, and robot pets. However, some robots were not clearly classified into a category. For example, Aibo, often referred to as a “robot dog”, was found to be more similar to Eilik than to Spot. Similarly, Neubie, which is shaped like a trolley or a locomotive, was more strongly connected with humanoid robots than with similarly shaped robots (e.g. Paryk) or other wheel-based robots (e.g. Pico and Astro).

The most distinct categories of robots are identifiable by cliques, which refer to fully connected components in the graph. We have highlighted the 4-cliques (4 fully connected robots) that exist in the graph, representing the categories of (A) robot pets, (B) humanoids, and (C) robot kids (in Fig. 3). The robot Nao falls into the category of children-oriented robots, which includes “robot pets” and “robot kids.” Thus, individuals evaluating Nao immediately associate it with the user-base and usage. In contrast, Neubie’s indefinite body image makes it challenging to connect it to a particular user-base or usage. Overall, the identified robot categories based on their semantic relationships suggest that people tend to form body images based on the anticipated user-base and usage of the robot, rather than its shape.

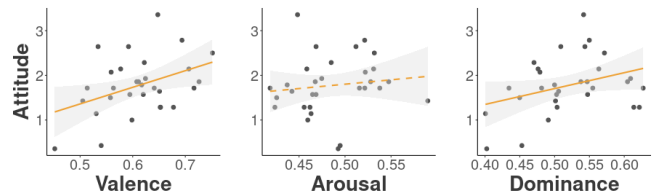


Fig. 1. The relationships between the attitudes and dominance, valence, arousal. The dashed line indicates the insignificance in the corresponding LME analyses.

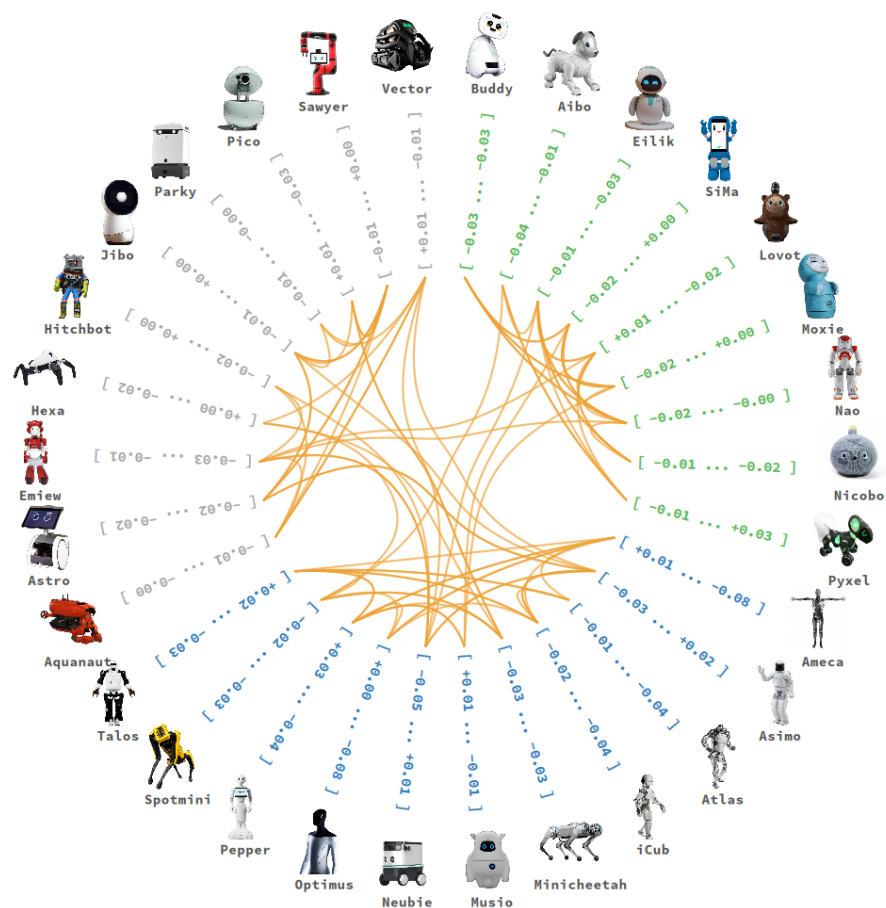


Fig. 2. Clustering of the robots based on their cosine similarities. The outermost circle is the robots in the present study. The intermediate circle indicates the vector abstraction of the robots, colored with the three clusters identified by hierarchical clustering of the cosine similarities between robots. And the innermost network is comprised of the connections between each robot and its 3 closest neighbors.

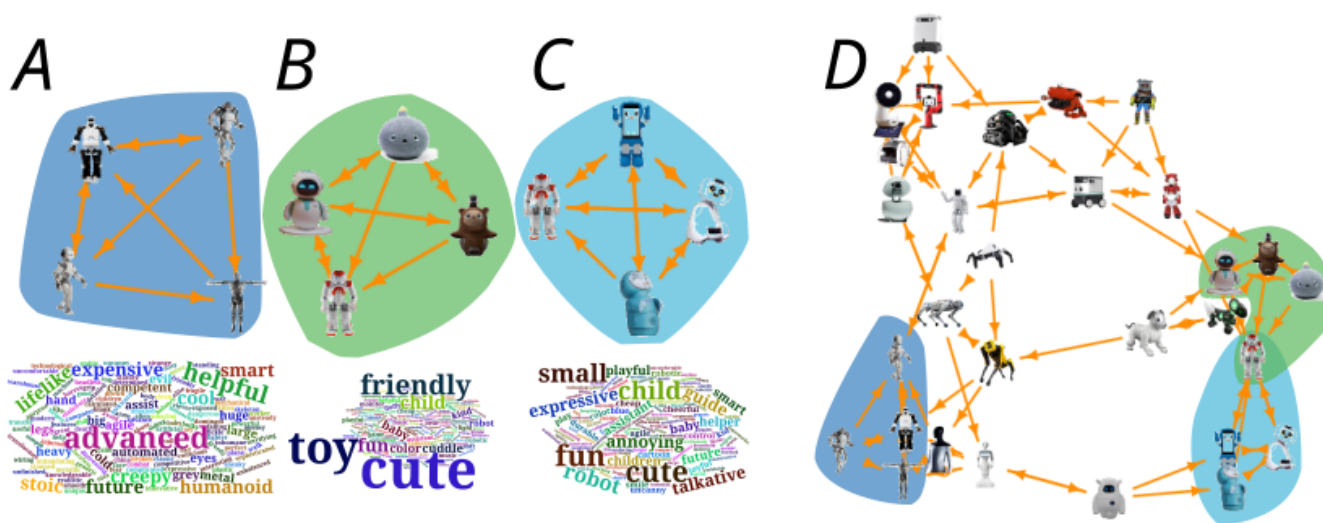


Fig. 3. The network of robots based on their body images. (A-C) Three 4-cliques in the network. (D) the whole network of all the 30 robots. The colors of the cliques correspond to the colors in the network.

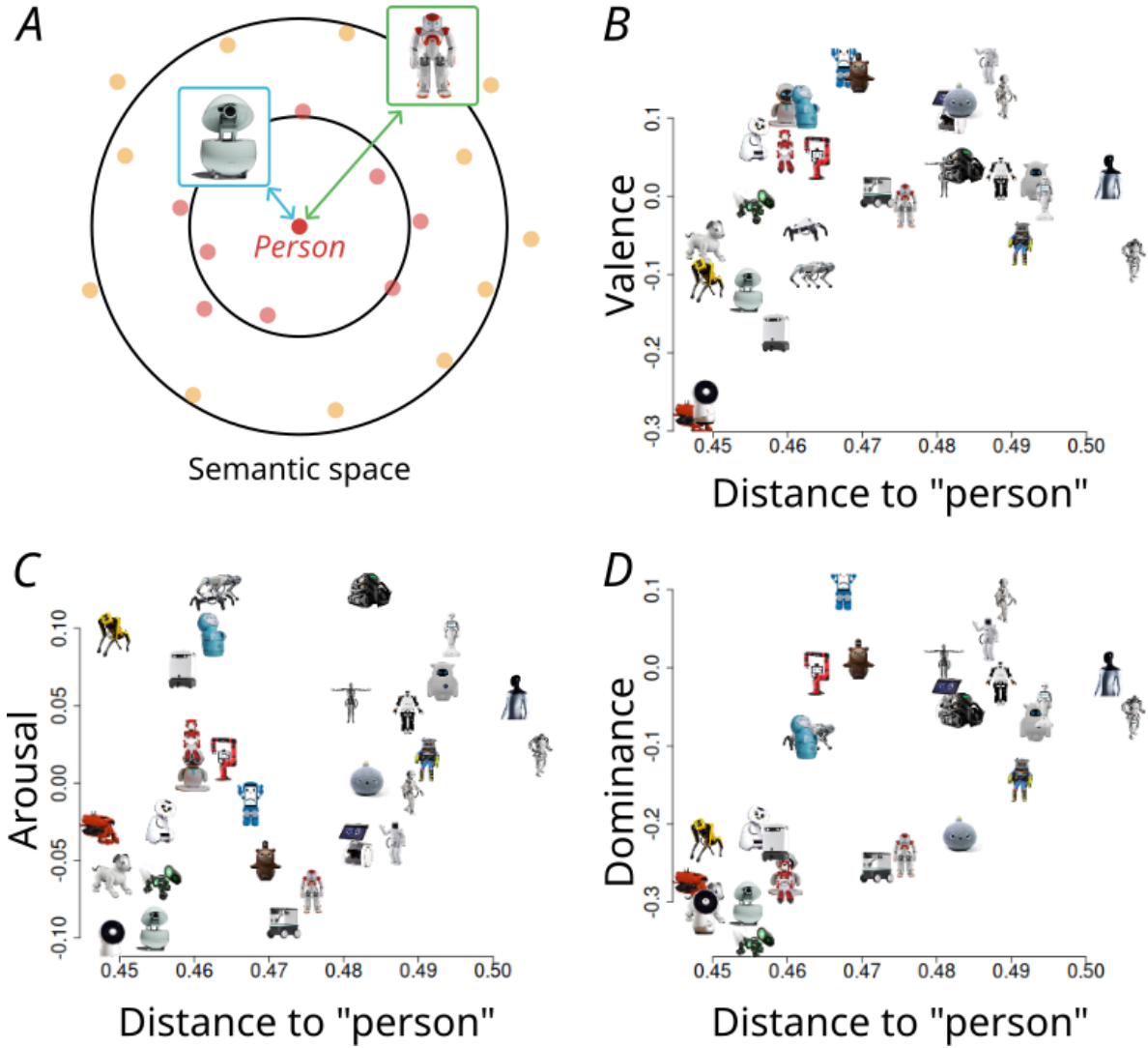


Fig. 4. The relationship between affects and human distance. (A) The diagram shows the distance between a robot and the target word “person”, simplified in a 2-dimensional plane for better illustration. The peripheral dots represent words in the original semantic space, the dots of the same color indicated in the vicinity of the circles around the word. The outer circle is the distance proximity of the robot NAO and the inner circle is the distance proximity of the robot Pico. Due to the bias towards the distance between words and human-related words, the words that are closer to the human-related words (the red dots) are systematically different from the words that are further than the human-related words (the orange dots). Therefore the affect values of the words on the proximity circles are used as baselines for the respective robots; (B-D) The x-axis is the distance between robot body images and the word “person”; the y-axes are standardized valence, arousal and dominance.

### C. The distance to human related words predicts affect of robots’ body images

The distance between a robot’s body image (the words that characterize the robot) and human-related words may provide insight into how closely the robot is associated with human life in a semantic sense. Here, we took the averaged word vectors for each of the robots, and computed their distance from the word “person” using the cosine distance. Specifically, we used the formula  $1 - \text{similarity}_{\cos}(v_1, v_2)$ , where  $v_1$  and  $v_2$  are the vectors abstracting a robot and the target word “person”.

Noteworthy, there are several human-related words sharing similar contexts from which we can choose, with a nuanced difference in their contexts though, including “adult”, “child”, “woman”, “man”, “human”, “people” and “person”.

We selected the word “person” as the target word due to the consideration that, primarily, this word has a context that is more general to human life. Since the training objective of Word2vec is to maximize the probability of the occurrence of a word given its context, or the occurrence of a context given its word, a word contains the information about the contexts where the word is commonly used. The context of the word “person” is also less discriminatory towards genders or age, which makes it a more representative term for human life.

Another consideration was that “person” has a larger number of words in proximity to the distance between it and the word vector that characterize the robot (see the dots of the same color indicated in the vicinity of the circles around the word “Person” in Fig. 4A). This helps to control for affective biases induced by the distance between human-



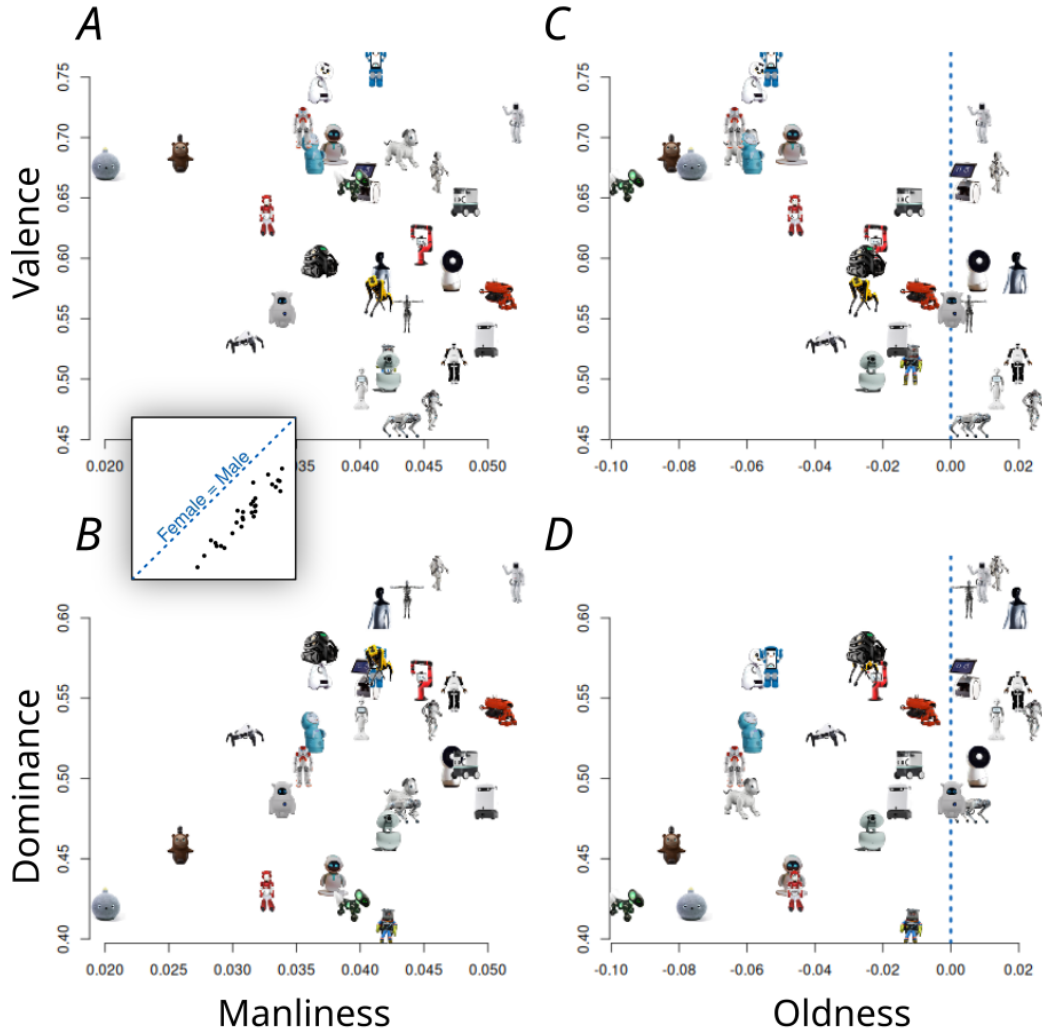


Fig. 5. The stereotypes about gender and age towards robots. (A) and (B) are the stereotype about gender; (C) and (D) are the stereotype about age; (A) and (C) are the relationships between the robot scores and valence; (B) and (D) are the relationships between the robot scores and dominance. The inset on the left side shows the positions of the robots around the sex equilibrium line, where the area below the equilibrium line is where male likeness score  $\geq$  female likeness score. The blue lines are the equilibrium lines splitting the sides of the opposing concepts.

related words and other words. An example of such a bias is the valence score of words, which is negatively correlated with the distance to the word “person”. The other affective scores of words (arousal and dominance) also tend to show systemic relationships with their distance to the target word “person”. To eliminate this bias, we subtracted a baseline from its affective score. In our analysis, a baseline for a robot was the mean affective level of all words at a similar distance between the robot and the target word (see 4A). There were fewer baseline words centered on the words “human” and “people” than on the word “person”, making “person” the most robust choice for the target word.

In Figure 4B-D, we analyzed the relationship between the perceived affective level (in terms of valence, arousal, and dominance) of robots’ body images and their distance from the target word “person”. Our results indicate that valence and dominance are both correlated with the distance to the target word. Specifically, the valence scores of words

associated with the robots initially increase with distance, then plateau with a slight drop at a level higher than the baseline. Similarly, dominance scores increase monotonously with distance to the target word. However, we did not find a clear relationship between arousal scores and distance to the target word.

Interestingly, we found that most of the humanoids were located further away from the target word “person” than the other robots. For example, Atlas, Optimus, Pepper, Musio, Hitchbot, Talos, iCub, and Asimo were the most distant robots, while Aquanaut, Jibo, Spot, Aibo, Pico, Pyxel, and Buddy were the closest. These results could suggest that being more human-like may not necessarily lead to better integration of robots into human environments.

#### D. The stereotypes about gender and age towards robots

Aside from the literal meanings of individual words, such as those related to humans, semantic space also incorporates

complex cultural and social associations that distinguish between opposing concepts. To investigate potential stereotypes as perceived by human participants, we utilized two sets of opposing concepts to analyze the body images of our robots.

The first set of opposing concepts examined the effect of gender, using words such as “females”, “female”, “girls”, “girl”, “women”, “woman”, “ladies”, “lady”, “actress”, and “actresses” for one end of the dimension, and “males”, “male”, “boys”, “boy”, “men”, “man”, “gentlemen”, “gentleman”, “actors”, and “actor” for the other end. The word vectors for each set were then averaged to respectively represent “female” and “male”, and this allowed for the positioning of the robots on the gender dimension. The results are presented in the left column of Fig. 5, where the upper plot shows the relationship between “manliness” and valence, and the lower plot shows the relationship between “manliness” and dominance. Note, the manliness scores on the x-axis were calculated by subtracting the distance between the robots to the female concepts from that to the male concepts, with greater values representing shorter distances to the male concepts. We found that manliness was positively related to dominance, and the humanoids were mostly on the more manliness side of the dimension. Notably, as shown in the inset, all robots were positioned on the male side of the semantic space, suggesting a stereotype of robots as males.

The second set of opposing concepts was about age, with one end consisting of the words “young”, “child”, “children”, and the other consisting of “old”, “elderly”, “adult”, “adults”. The results are shown in the right column of Fig. 5. We found that the humanoids were positioned closer to the “older” end of the age dimension, while the robot pets and robot kids were closer to the “younger” end. While this finding was in line with our expectations, we found that the robot vectors crossed the equilibrium line between young and old. This was a notable difference from the gender dimension, where no robot crossed the equilibrium line between female and male. The relationship between “oldness” and valence on the one hand, and “oldness” dominance on the other hand shows that robots that are perceived as older have lower valence scores and are perceived as more dominant.

#### IV. DISCUSSION

The field of psycholinguistics provides a wealth of knowledge about the nature of words. In this study, we introduce a paradigm that leverages this knowledge to investigate human-robot interaction. Specifically, we analyzed the words associated with the visual image of robots to gain insight into human perception of them. We found that the affective connotations of these words (valence and dominance) are predictive of people’s attitudes towards robots. Additionally, we were able to group robots based on their intended user-base and appearance, using the associated words as a guide. A third key finding underscored the importance of a robot’s body image in shaping its potential integration into the human environment. Specifically, we found that humanoids were often positioned further away from the target word “person” than other types of robots, suggesting

that being more human-like may not necessarily lead to better integration into human environments. Lastly, we used opposing concepts to characterize our robots on the gender- and age-dimensions, with a notable finding that our robots were associated more with words pertaining to masculinity, which was correlated with dominance.

Our paradigm consists of two procedures. The first procedure involves associating robots with a set of words, which allows us to infer the perceived emotions of the robots based on the degree of valence and the degree of dominance of the words as determined in existing lexicons (e.g., Mohammad’s 2018 [11]). Fig. 1 demonstrates how word-related valence and dominance can be utilized to predict human attitudes towards robots obtained from Likert scale ratings. Note, a recent study on social robots [17] also employed free association to investigate participants’ word associations with the written word “robot” and used factor analysis to categorize the mental representation of robots as social entities. Our study shares a similar theoretical foundation with this prior research, but with a more specific focus on individual robots rather than a general robot concept or its social presence.

In the second procedure, the words associated with the robots are transformed into 300-dimensional vectors, representing the robots in a robust semantic space. Fig. 3 shows that although the grouping of robots is based on their associated words, members of a group also exhibit similarities in their physical appearance and derived features. For example, humanoid robots are grouped around the blue clique on the left side of the figure, next to the quadrupedal robots, while child-oriented robots are clustered in the green and light blue cliques. As the number of robots increases, these patterns are likely to become even clearer. These findings provide support for the idea that a robot’s body image comprises interconnected visual, semantic, and potentially social features, which are all inferred from the robot’s morphology.

Our paradigm allows for a rich description of how humans perceive robots, with the potential for exploring various lexical and semantic features. This detailed understanding can shed light on the ways in which robots relate to one another and to other concepts within the semantic space. This can be done by two approaches. Firstly, by computing the distance between the robots to words that encompass a broad context in semantic space, i.e. “person”, we exhibited how valence and dominance are related to a robot’s proximity to the concept of “person” (Fig. 4). Secondly, by computing the distance between the robots and features such as gender and age in semantic space, we exhibited how people anthropomorphize, and even disambiguate, robots. This analysis revealed that the set of robots used in our study was generally perceived as more masculine, and robots that were perceived as younger had a more positive valence (Fig. 5). These results highlight the importance of a robot’s body image in shaping its interactions with humans and its potential integration into human environments.

Finally, our study provides valuable insights for commercial robot development, as we discovered that human



attitudes towards robots can be predicted from the valence and dominance of the words associated with them. For example, robots such as Jibo and Buddy, which are low in dominance and closer to the concept of “person”, may be more appealing for consumers compared to humanoids. As we continue to expand our dataset of robots, we anticipate even greater insights into the complex dimensions of robots and their impact on human behavior and response.

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