# Public Perception of Android Robots

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# Public perception of android robots: Indications from an analysis of YouTube comments

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***Abstract*— The public perception of android robots is a field of growing applied relevance. Currently, most androids are confined within controlled environments rendering interactions between potential end-users, and robots challenging. Even more challenging is for researchers to investigate end-users' perception of androids. We exploit pre-existing YouTube comments as artifacts for quantitative content analysis to gain an indication of social perception on androids. We perform a content analysis of 10301 YouTube comments from four different videos, and reflect on the textual reactions to video stimuli of four extremely human-like android robots. We use text mining and machine learning techniques to process and analyze our corpus. Our findings reveal three equally important topics that should be considered for paving the way towards a robotic society: human-robot relationships, technical specifications, and the science fiction valley. Considering people's attitudes, fears and wishes towards androids, researchers can increase citizen awareness, and engagement.**

## I. Introduction

Human-Robot Interaction (HRI) can uncoil and expand in many ways, and one of these is with android robots. An android is a robot designed to appear like a human in terms of form, behavior, intelligence, motion, and communication [1 - 4]. These anthropomorphic robots are exploiting the same brain functions that humans use to understand other human beings [5]. In this manner, social norms and expectations are applied automatically, and carelessly to such robots [6]. The prior affective interface of androids is their face, which naturally conveys messages on the robots' identity, gender, age, race, and attractiveness, but also transmits emotionally relevant information through its static signals, which are the permanent aspects of the face (i.e., morphological/bone structure, skin pigmentation, location of facial features) [7].

Uncertainty and insecurity connected with meetings of the unfamiliar -in our case an android robot- might not be settled at an instant. It might be a process negotiated over time, while the mind tries to come to terms with the fact that the presence before them cannot be solely accounted for neither as a robot, nor as a human being. In a study conducted by Saygin et al. [8], they used functional magnetic resonance imaging (fMRI) to explore the selectivity of the human action perception system when encountering an android. The outcome of their research reports a mismatch between the human-like appearance and the mechanical motion of androids, leading to a larger prediction error, which is manifested as activity in relevant brain regions. Interaction with androids is influenced by both mechanical and organic conceptions of what an android is. When meeting a human-size anthropomorphic robot with detailed facial features it would be reasonable to assume that some interaction partners would place emphasis on the human aspect of the robot, while others may focus on the mechanical aspect of the robot. Within a brief period of time, interaction partners from both sides would be "enforced" to deal with the other condition as well. Supposing that androids had personality, it should be a mixture of human personality (the pattern of collective character, behavioral, temperamental, emotional and mental traits of an individual that have consistency over time and situation) and product personality (the set of human features related to a product created by industrial design, and most of the times also with a brand) [9 -11].

During these interactions, a question that rises is: "How can we understand and describe what happens when humans are engaged in meeting an android?". A deeper insight into public perception of androids could assist researchers in designing better robotic interfaces, developing new features to equip the robots, and establishing durable HRI. The robotic community can learn a lot by taking into consideration people's expectations, attitudes, fears and wishes towards androids, and researchers can find ways to increase citizen awareness, and engage the end-user. If we envision a robotic society, then we should plan for it, and prepare citizens for it. Currently, the few androids that exist can be encountered "in the wild" mainly at museums, theaters and exhibitions [12 - 16], while the majority of them is confined to research labs.

Faced with the challenge of collecting reactions to androids to measure public perceptions and awareness, we resorted to making use of the thousands of comments that appear on YouTube videos showing androids. Interacting with a real robot, and watching a video with a robot are two different situations that may lead to differences in the representation of the robot. However, researchers can use the reactions to video stimuli to gain an indication of how the public perceives the androids. A trend, or a hidden pattern that is observed in big data analysis can potentially uncover insights that haven't been noticed before. The advantage of such a corpus is that the YouTube comments are more spontaneous and less regulated compared to other social media networks (e.g., Facebook) that present a more egalitarian distribution between discussants and a higher level of politeness [17]. YouTube comments are also more rewarding compared to standard questionnaires where subjects are usually college students paid to participate. YouTube is the second most visited site on the web [18] with over a billion users — almost one-third of all people on the Internet — and people spend hundreds of millions of hours

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every day watching and commenting on YouTube videos [19]. YouTube is perhaps the largest platform for disseminating content to a very broad audience comprised of both amateur content creators and professional companies [20] and has been used numerous times as a research tool [21 - 24]. Recent research [25] indicated that the motives for participation on YouTube in descending order according to importance are: relaxing entertainment, social interaction, information seeking and giving information. However, Shao [26] claims that YouTube visitors seeking information about androids want to "increase awareness and knowledge of one's self, others, and the world" about topics related to android robots.

We apply text mining and machine learning techniques to process and explore the data to gain an indication on how people perceive android robots by identifying the topics that emerge from the comments analysis. In the following sections, we explain our methodology, present the results and their analysis, discuss our findings and conclude with possible limitations and future work.

## II. Method

### A. Stimulus Material

We selected to analyze the comments from four YouTube videos showing four different androids (two female and two male) of two major android creators; Hiroshi Ishiguro Laboratories in Japan represented with Geminoid-F and Geminoid-DK, and Hanson Robotics in U.S.A. represented with Sophia and Jules. Table 1 presents detailed information regarding the selected videos[1], and Figure 1 shows screenshots from the videos depicting the four androids. In all videos, the androids are either engaged in conversation, or portray various emotions via their facial expressions. The four videos of roughly 11 minutes total duration time had generated traffic in excess of 9,7 million views and 10301 comments by the time they were accessed, rendering them significant enough to investigate.

TABLE I. DETAILS ON THE SELECTED YOUTUBE VIDEOS*

| Robot Video | Published | Comments | Views | Likes/ Dislikes | Time (sec) |
|---|---|---|---|---|---|
| Geminoid-F | 2012 | 1338 | 1235345 | 2267/136 | 164 |
| Sophia | 2016 | 6534 | 5203009 | 15459/2992 | 157 |
| Geminoid-DK | 2011 | 754 | 2401413 | 2340/74 | 54 |
| Jules | 2006 | 1675 | 889273 | 2437/104 | 309 |

*Accessed: 14th of October 2016.

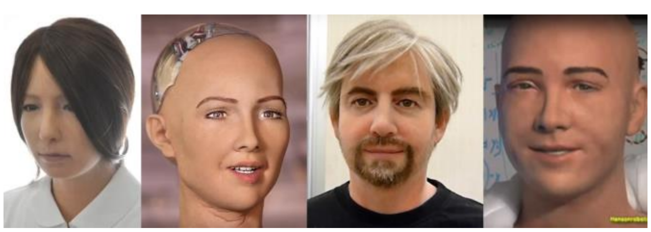

Figure 1. Screenshots from the videos depicting the four androids: Geminoid-F, Sophia, Geminoid-DK, and Jules (left to right).

[1] Links to the videos:
Geminoid-F: https://www.youtube.com/watch?v=cy7xGwYdRk0
Sophia: https://www.youtube.com/watch?v=W0_DPi0PmF0
Geminoid-DK: https://www.youtube.com/watch?v=eZlLNVmaPbM
Jules: https://www.youtube.com/watch?v=ysU56JzBjTY

### B. Procedure

In a less dense corpus, lattice theory or a Formal Concept Analysis technique could be applied [27] for exploring the comments by reading through them and manually applying themes to each one. Due to the large amount of comments we resorted to text mining and machine learning techniques with the use of R free software environment for statistical computing.

*Text corpus collection:* We first set the comments list in chronological order following the YouTube option "Newest first", and then expanded the comments list using the option "Show more" until there was no other comment left to show. When there were replies available for a comment we always selected the option "View all replies", and if the content of a comment extended beyond the five standard lines YouTube uses as visible space for comments, we always selected the option "Read more" to reveal the full content. Finally, we exported all the comments as a text file. This procedure was followed for all four videos leading to a corpus of four text files.

*Text corpus preprocessing:* In order to prepare the corpus for analysis, we needed to preprocess the files as follows [28, 29].

- Remove all punctuation and special characters (e.g., "@", "/", "_" etc.)
- Remove numbers.
- Remove words that have no analytic value (e.g., "a", "and", "also", "but", "I", "or", "she", "the", etc.) which appear frequently, and perplex the analysis if they remain.
- Remove particular words that YouTube is using as terminology, and are frequent in the files like "comment", "day", "days", "month", "months", "year", "years", "ago", "edit", "hide", "reply", "replies", "just", "now", etc.
- Remove unnecessary white space.
- Stem the files by removing common word endings such as "-ing", "-es","-s", so that a word can be recognizable to the software despite the possible endings it might have in the text.
- Convert all text to lowercase characters for uniformity.
- Textual reactions that could be classified as humoristic, or ironic were not filtered out from the corpus as these are genuine reactions that people would make even in direct human-android interaction. According to Garas [30], the activity patterns and behavior of humans seem to remain unchanged across online and offline communication channels.

*Text corpus analysis:* We applied text mining and unsupervised learning techniques [31 – 33] to analyze our preprocessed corpus. After processing our data, we explored them as follows.

- Find the significant words that appear on all four files, and remove the words that are present due to coincidence and have very low frequency.
- Find the most frequent occurring significant words.
- Cluster the words that appear together in comments across all four files into groups.
- Identify the topics that emerge from the clusters of the comments.

Text files are unstructured data, meaning they enclose information in a not organized and predefined manner, therefore exploration and analysis is only possible when the text is transformed into structured data with high level of organization (i.e., a matrix). We use the unsupervised method of Principal Component Analysis (PCA) to provide visualizations of our corpus by means of dimensionality reduction "in which a number of related variables are transformed to (hopefully, a smaller) set of uncorrelated variables" [34]. The goal of PCA is to identify the most meaningful way to extract the important information from a corpus described by several dependent inter-correlated variables, and to re-express this information -by filtering out the noise and revealing hidden structure- as a set of two new orthogonal variables called principal components [35, 36].

Clustering is an unsupervised learning technique that aims to find patterns and structures in a collection of large data sets with no background knowledge [37]. The two main clustering methods are the hierarchical type that creates a dendrogram tree structure representation of the data which is not optimal for large data sets, and the partitioning type - which we will apply - that divides the data into homogeneous clusters [38]. In our case, a cluster would consist of words that would be "similar" in terms of relevance – meaning that they appear together in comments- and dissimilar to the words belonging to other clusters. From the numerous clustering algorithms that exist in the literature, considering the type of our data, we chose to use the *k-medoids* algorithm. K-medoids is a robust to noise and outliers algorithm that minimizes the sum of dissimilarities between words belonging in a cluster and a word –the medoid- designated as the most centrally located point of that cluster [39]. We will use the most common approach to perform k-medoid clustering, that is the Partitioning Around Medoids method [40]. The optimal number of clusters, as well as the quality and accuracy of clustering, can be determined by the *Average Silhouette Width* criterion. A silhouette is based on the comparison of the tightness and separation of each cluster, and shows which words fit well within their cluster, and which ones do not [41]. A high silhouette value (silhouette width lies between -1 and 1) above the threshold of e.g., 0.71 indicates that the word is well situated to its assigned cluster.

The number of clusters that will be created by the clustering algorithm will then determine the number of topics that can be identified while "reading" through the comments, and with a topic modeling algorithm we can discover the hidden thematic structures of our corpus. We use the *Latent Dirichlet Allocation* probabilistic model and the variation expectation–maximization algorithm for modeling text corpora to represent our corpus as a mixture of topics comprised of words with certain probabilities [42]. A topic is formally defined as a distribution over a fixed vocabulary containing words with high probability [43].

## III. Results

After the text corpus preprocessing we found 16857 words appearing 22880 times with 66% sparsity in the four files, a very large amount of words to handle. Sparse words are words that only occur very few times in few of the documents. Further filtering for removing sparse words, without losing significant information though, left the corpus with 694 unique words that appeared 2776 times with 0% sparsity. Figure 2 presents a frequency plot for the unique words that appear more than 170 times in the corpus. The ending of some words is cut due to the stemming filtering.

The three main topics of discussion that emerged by scanning through the data are presented at Table 2. The words follow an ascending order of specificity, meaning that the word "woman", for example, in the first topic is more specific than the word "like". We have selected to present a depth of thirty words per topic as representative of the identified themes within a topic. Words that are typeset in

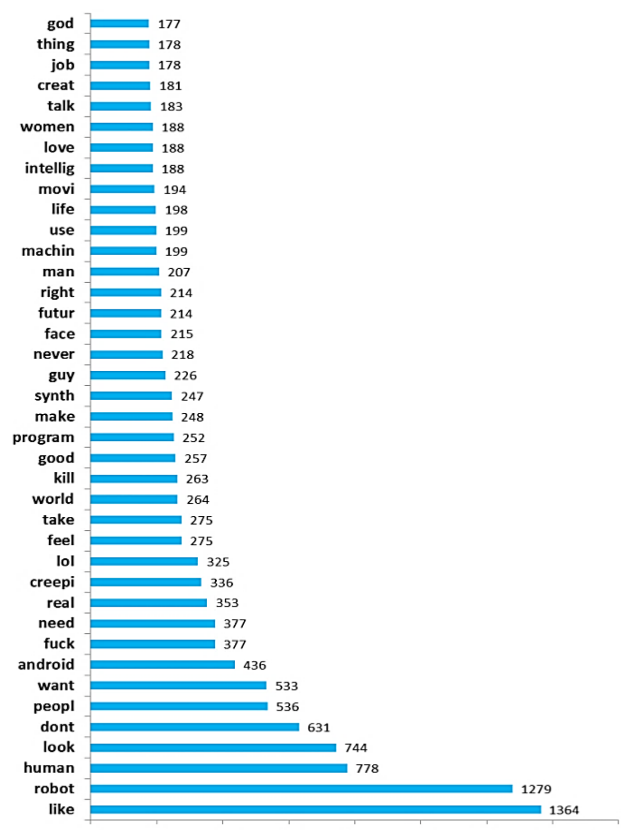

Figure 2. Frequency plot for words that appear more than 170 times.

boldface appear only on one topic, and perhaps are the words that define the topic.

Last, but not least, before we discuss the results in the following section we should be reminded that with a percentage of 86% (n: 22503) "Likes" and 14% (n: 3306) "Dislikes" in total (see Table 1) we can safely state that the commenters took an overall optimistic stance towards the androids, or towards being educated about androids, or towards being entertained with the androids.

## IV. Discussion

The aim of the discussion section is to find meaningful ways to interpret the results, and communicate the main outcomes of the study. Reading through the keywords in Table 2, we can make some inferences on what the three primary, and equally important topics that emerged could be. Our findings appear to bear some similarities with the outcome of a recent study by Katz and Halpern [44] on attitudes towards robots based on appearance that also revealed three main attitudes: Robot-Liking that is related to social companionship, Robotphobia and Cyber-Dystopianism. Another study [45] analyzing views about artificial intelligence in the New York Times over 30 years revealed that interest increased since 2009, and confirmed our finding that the discussions have been consistently more optimistic than pessimistic. However, they found that topics like loss of control, ethical concerns, and the negative impact of AI on work have grown in recent years.

### *A. Human – Robot Relationships*

With unique words like "women", "men", "sex", "love", the dominant theme of topic 1 (Table 2) could be labelled as "human-robot relationships" which is leaning towards an organic conception of what an android is. Independent of the gender of the robot, there are individuals who, for various reasons, would enjoy the company of androids. As Turkle [46] argues, such individuals can be seen as early adapters who provide a future view of the human-robot close relations. Notable instances of robotic advances towards the human-robot love direction are: a kissing machine that reproduces and transmits the haptic sensations of kissing [47], the humanoid buttocks that communicate emotions via visual and tactual transformation of the muscles [48], a multi-modal sentimental systems aiming to generate bi-directional love between humans and robot [49], and finally the establishment of a scientific field called Lovotics that explores the bidirectional human-robot love. Yeoman and Mars [50] in their paper "Robots, men and sex tourism", described a futuristic scenario where by 2050 robot sex would have solved problems associated with the sex trade, including human trafficking and sexually transmitted diseases. A recent web-based survey [51] showed that android robots were rated high on familiarity and likeability, whereas other humanoid less anthropomorphic robots were rated as threatening, rendering androids more lovable. Currently, researchers are initiating actions on alerting the robotic community and the public by proposing "ethical limits on the manipulation of human psychology when it comes to building sex robots and in the simulation of love in such machines" [52] by forming responsible robotics foundations to "promote the responsible design, development, implementation and policy of robots embedded in our society" [53], and by even creating campaigns against sex robots to prevent inequalities in society [54].

TABLE II. Identified Topics In The Corpus By A Latent Dirichlet Allocation Probabilistic Model And Their 30 Most Frequent Words In Ascending Order Of Specificity*

| Topic 1 | Topic 2 | Topic 3 |
|---|---|---|
| "like" | "robot" | "like" |
| "dont" | **"want"** | "human" |
| "fuck" | "like" | "robot" |
| **"women"** | "look" | **"program"** |
| "look" | "human" | **"feel"** |
| "human" | "android" | "look" |
| "real" | **"synth"** | "dont" |
| **"men"** | "dont" | "peopl" |
| "android" | **"creepi"** | "real" |
| "peopl" | "peopl" | "lol" |
| **"sex"** | "need" | "world" |
| **"man"** | "kill" | **"hes"** |
| **"love"** | "take" | "good" |
| "robot" | **"job"** | **"talk"** |
| "need" | "face" | **"doesnt"** |
| "read" | "futur" | **"emot"** |
| **"use"** | **"skynet"** | "life" |
| **"your"** | **"right"** | **"movi"** |
| "never" | **"uncanni"** | "make" |
| **"lord"** | "lol" | "need" |
| **"first"** | **"termin"** | **"hope"** |
| "lol" | **"end"** | "fuck" |
| "guy" | "fuck" | "kill" |
| **"girl"** | **"machin"** | "face" |
| "good" | "make" | "never" |
| "world" | "guy" | **"sound"** |
| "futur" | **"help"** | **"comput"** |
| "take" | **"valley"** | **"express"** |
| "life" | **"god"** | **"question"** |
| **"give"** | **"thing"** | **"head"** |

** Words that appear only on one topic are typeset in boldface.*

### *B. The science fiction valley*

With words like "want", "synth", "creepi", "job", "skynet", "uncanni", "termin", "end", "machin", "help", "valley", "god", "thing" the dominant theme of topic 2 (Table 2) could be labelled as "the science fiction valley" which is influenced by both the mechanic (e.g., the uncanny valley hypothesis) and the organic (e.g., quotes from and allusion to science fiction movies and games) conception of what an android is. In 1970 Mori formed the hypothesis of the uncanny valley suggesting a non-linear relationship between human likeness of robots and human familiarity towards them [55]. The hypothesis is fundamentally concerned with what happens at an instance, and has not been officially confirmed. Despite that fact, the uncanny valley is a direct reference to terminology used in robotics. Creepiness (appeared in 336 times in the comments – see

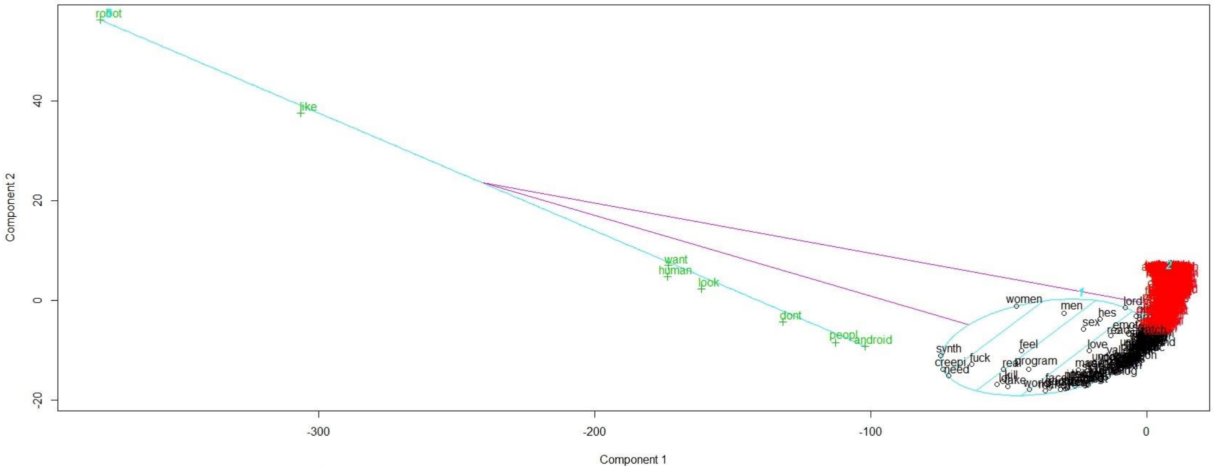


Figure 3. Principal component analysis (98.97% of total variance) of the 694 unique words that can discriminate the corpus in the three thematic clusters: The first cluster is in the ellipse, the second cluster is in the red area, and the third cluster is on the diagonal green line.

Figure 2) and other reactions of revulsion did occur for some visitors when exposed to the android videos, and these reactions were combined with scenarios influenced from science fiction novels, films and games speaking of robots killing humans ("kill" appeared in 263 comments), the end of the world narrative, or the classic stock phrase "god help us all" when horrific events happen ("god" appeared in 177 comments). The word "synth" appearing 247 times is a term taken from the post nuclear roleplaying video game "Fallout", and is diminutive for synthetic humanoids that are designed to look, function and behave like humans[2]. The word "skynet" that appears further down in topic 2 list of specificity, is taken from the science-fiction movie "The Terminator" a self-aware automated defense network, which turned against humanity when attempts were made to shut it down. A recent study on android robots [56] claimed that reading a science fiction story prior to HRI could reduce the creepiness of the androids, but the study failed to highlight the importance of a positive end-of-story, which deviates from the movie scenarios. Lastly, the combination of words "take" and "job" ("job" appeared in 178 comments), is a direct reference to human experience, and increasingly relevant to human welfare, since people feel the threat of unemployment due to technological change.

### *C. Technical Specifications*

With words like "program", "feel", "talk", "emot", "life", "movi", "hope", "sound", "comput", "express", "question", "head", the dominant theme of topic 3 (Table 2) could be labelled as "technical specifications" which is leaning towards a mechanic conception of what an android is. The words used in this topic contain direct references to terminology used in robotics/programming/science including the current state-of-the-art, advice on how to improve the androids, technical questions on the functionalities of the robots, and hopes for future improvement. In general, this topic deals with opinions on whether people are pro/con on such technological advancements, accompanied with various positive or negative remarks describing pleasure, enjoyment, dissatisfaction, and even destruction of the robot.

## V. CONCLUSION

Our goal was to deepen the robotics' community understanding on people's perceptions regarding androids by analyzing thousands of textual reactions to YouTube videos of different robots. Human-robot relationships, science fiction narratives, unemployment, and recommendations on technical specifications were the topics that dominated the comments. Our findings provide the basis for a strong indication on what the public thinks, fears, and wishes regarding android robots, and their function in society. Attending to people's expressed anxieties, we believe that we can increase citizen awareness and participation in the field of robotics, and prepare them for future co-existence.

Several limitations of the study need to be addressed. We only analyzed four videos and dealt with the perception of only four android robots. Even though our selection of robots is quite representative of the range of androids, it is definitely not an exhaustive sample. Another limitation is that we did not take into consideration the modulation of attitudes over time which could provide significant information on how public perception of androids is changing. It would be interesting to control the cultural or the gender effects in a future study and examine the differences. Future investigations into these matters could broaden the empirical base, assist in the discovery of more core themes possibly in other dimensions than the one investigated here, and perhaps even assist in predicting future attitudes.

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