Audio-visual predictive processing in perception of humans and robots

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Abstract

Recent work in cognitive science suggests that our expectations affect visual perception. With the rise of artificial agents in human life in the last few decades, one important question is whether our expectations about non-human agents such as humanoid robots affect how we perceive them. In the present study, we addressed this question in an audio-visual context. Participants reported whether a voice embedded in a noise belonged to a human or a robot. Prior to this judgment, they were presented with a human or a robot image that served as a cue and allowed them to form an expectation about the category of the voice that would follow. This cue was either congruent or incongruent with the category of the voice. Our results show that participants were faster and more accurate when the auditory target was preceded by a congruent cue than an incongruent cue. This was true regardless of the human-likeness of the robot. Overall, these results suggest that our expectations affect how we perceive non-human agents and shed light on future work in robot design.

Keywords: prediction, expectation violation, human-robot interaction, audio-visual mismatch

25   **Introduction**

26   Advances in artificial intelligence in the last few decades have introduced us to humanoid
27 robots that we encounter everywhere ranging from classrooms to airports to shopping malls to
28 hospitals. While their presence in our daily lives has brought a lot of excitement, how humans
29 perceive and interact with them has become an important research topic in cognitive science. Do
30 we perceive them differently from the way we perceive other humans? How important is it that
31 they look or sound human or behave like humans? What are our expectations from robots? To
32 what extent do they fulfill our expectations? These are some of the questions cognitive scientists
33 are interested in addressing not only to be able to better understand human nature but also to be
34 able to guide the design of robots in the future.

35   In his classical work, *The Design of Everyday Things*, Don Norman (2013) provides
36 important insights about how cognitive sciences can help in the design of artefacts including
37 machines such as robots. According to Norman (2013), the design artifacts should be adapted to
38 the minds of their users and this is why one needs to understand the human mind first. This
39 implies that a collaboration between human-robot interaction and cognitive sciences is necessary.
40 Indeed, the use of robots in well-established cognitive psychology and neuroscience paradigms
41 in the last decade has proven useful to understand how humans respond to non-human agents
42 as compared to their human counterparts, and what kind of principles we should follow in
43 humanoid robot design (MacDorman and Ishiguro, 2006; Cross et al., 2019; Cross and Ramsey,
44 2020).

45   One of the cognitive psychology/neuroscience paradigms that have been successfully
46 applied in human-robot interaction is expectation-violation paradigms (Saygin et al., 2012; Urgen
47 et al., 2018). These paradigms have been developed to understand the nature of information
48 processing in a variety of perceptual and cognitive tasks (Kutas and Hillyard, 1980; Kutas and
49 Federmeier, 2011; Kok et al., 2013; Kok and de Lange, 2015; de Lange et al., 2018; Urgen and
50 Boyaci, 2021) and have been instrumental to come up with recent theories of human brain and

cognition such as predictive coding or computation (Friston, 2010; Clark, 2013, Heeger, 2017). According to these theories, perception is not a purely bottom-up or stimulus-driven process, rather, expectations and prior knowledge play an important role in how we perceive our environment. A growing body of empirical work in psychology and neuroscience are in line with these theories showing that participants respond faster and more accurately when they perceive events that are expected compared to the ones that are unexpected (Kok et al., 2013; Kok and de Lange, 2015; de Lange et al., 2018). These results suggest that humans constantly predict what would come next and this in turn determines what they perceive.

Recent work at the intersection of cognitive science and social robotics has shown that humans can extend their prediction skills to perception of robots and form expectations about robots based on their prior experience (Ho and MacDorman, 2008; Saygin et al., 2012; Urgen et al., 2018). These studies manipulated expectations towards robots by means of using stimuli that have mismatches in a variety of visual dimensions including appearance (form), motion, and interaction. In other words, these mismatch paradigms aim to induce certain expectations based on a particular cue, and at the same time present another cue that usually does not match with that cue, resulting in expectation violation. For instance, Urgen et al. (2018) show that the appearance of a robot can elicit certain expectations in humans about how the robot would move, and when the robot does not move in the expected way, an N400 effect is observed indicating that the expectations are violated.

Other studies explored mismatches in multisensory context including the congruity of appearance and voice (Mitchell et al., 2011; Hastie et al., 2017; Cabral et al., 2017; Stein and Ohler, 2018; McGinn and Torre, 2019). One drawback of these studies is that they usually use subjective measures such as fear and eeriness (Mitchell et al., 2011), credibility or attractiveness (Stein and Ohler, 2018), politeness and lifelikeness (Hastie et al., 2017), likability, expressiveness, and understandability (Cabral et al., 2017), drawings (Mara et al., 2020), or emotion labeling (Tsiourti et al., 2019) to evaluate artificial agents rather than more objective measures such as

reaction time or accuracy, which would be more informative about the basic perceptual processes. Hence, how expectations affect perception of robots in a cross-modal audio-visual context remain unknown.

The aim of the present study is to investigate whether we make predictions about how robots *sound* based on how they *look*, and whether those predictions are similar to the ones we make for humans. To this end, we used an expectation-violation paradigm in which human participants judged whether a greeting word sounded human-like or robotic. This sound was preceded by a picture of a human or a robot and informed the participants with a certain probability about the sound that would follow (thus form expectations). The hypothesis is that people would perceive robot sounds faster when they are preceded by a robot picture in contrast to a human picture just as they would do so with human sounds that are preceded by human pictures. Our results confirm this hypothesis suggesting that we could develop certain expectations about how robots behave (e.g. sound like) based on their appearance, similar to our expectations about our human companions.

Method

Participants

30 healthy adults from Bilkent University (16 females, Mean age = 25.2, SD = .65) participated in the experiment. All participants had normal or corrected-to-normal vision and hearing. The sample size of the study was determined by a power analysis prior to data collection. The minimum required sample size was determined to be 30 by using G*Power (with alpha = 0.05, beta = 0.90, $\eta^2 = 0.25$). Before the experiment, all subjects signed a consent form approved by the Human Research Ethics Committee of Bilkent University.

Stimuli

Visual Stimuli: The visual stimuli consisted of static images of three agents. We call them Human, Android, and Robot (See Figure 1). Android and Robot are the same machine in different appearances. Android has a more human-like appearance, and was modeled from the Human agent, whereas Robot has a more mechanical appearance as the clothing is removed. Android is the robot Repliee Q2 which was developed at Osaka University. The images in Figure 1 were captured from the videos of Saygin-Ishiguro database (Saygin et al., 2012; Urgan et al., 2018), the agents were doing hand waving gesture. The images were 240 x 240 pixels in size, and all three were matched in terms of their low-level properties (luminance and spatial frequency) with SHINE Toolbox (V. Willenbockel et al., 2010).

Figure 1. Visual stimuli in the experiments consist of images of three agents with different degrees of human-likeness: a human (Human), and two robots, one having more human-like appearance (Android) and one having less human-like appearance (Robot).

Auditory Stimuli: The auditory stimuli consisted of two sound files which lasted 2 seconds: the voice of a human saying 'Good morning' (Human Voice), and a modified version of it in which the voice sounds robotic (Robotic Voice). To make the natural human voice robotic, we used an audio library (AudioLib) in Python (Peirce, 2019). We used the settings of the "Ghost" option in this library to create the robotic voice. To compensate for the echo factor in the robotic voice, echo (0.05) was added to the human voice. Audio files were matched in terms of their amplitude using

the Adobe Audition CC (13.0.6). We also added white noise to both sound files to make the task harder, as previous research on prediction shows that the effect of prediction is strongest when the stimulus is ambiguous (Lange et al., 2018).

Procedure

Subjects participated in two experiments (Experiment 1 and Experiment 2). The order of the experiments was counterbalanced across subjects. In both experiments, the subjects were seated 57 cm away from a computer screen. Their heads were stabilized with a chin-rest. Before each experiment, the subjects were introduced to the visual and auditory stimuli, and were given verbal instructions. In particular, the human voice was told to belong to the human in the Human image, and the robotic voice was told to belong to the agent in the Robot or Android image depending on the experiment. They also did a practice session to make sure that they understood the task. The experiment was programmed in Psychtoolbox (Brainard, 1997; Pelli, 1997).

Experiment 1: Experiment 1 consisted of 5 blocks, each containing 80 trials. Each trial started with a fixation cross on a gray background (1 sec), which was followed by a visual cue (1 sec), an image of a human or a mechanical robot (Human and Robot agents in Figure 1). Following the visual cue, a 2 sec auditory stimulus was presented, either a human or a robotic voice (See Figure 2). The task of the subjects was to indicate whether the sound was human-like or robotic by pressing a key.

Figure 2. Each trial in Experiment 1 consists of a fixation screen, a visual cue (Human or Robot) and an auditory target (human or robotic voice) after which subjects need to respond with a key press.

The visual cue informed the subjects about the upcoming auditory stimulus category. In 80% of the trials, the visual cue was congruent with the auditory stimulus (e.g. human image and human voice or robot image and robotic voice), whereas in 20% of the trials, the visual cue was incongruent with the auditory stimulus (e.g. human image and robotic sound or robot image and human voice, see Figure 3).

Figure 3. There are two types of trials in Experiment 1. A. Congruent trials in which the category of the visual cue and the auditory target match (e.g. human appearance (Human) and human voice, or robotic appearance (Robot) and robotic voice), B. Incongruent trials in which the category of the visual cue and the auditory target do not match (e.g. human appearance (Human) and robotic voice, or robotic appearance (Robot) and human voice).

Experiment 2: Experiment 2 is identical to Experiment 1 except the visual cue screen. As a visual cue, subjects were shown the image of either a human or a human-like robot (Human and Android agents in Figure 4).

Figure 4. Each trial in Experiment 2 consists of a fixation screen, a visual cue (Human or Android) and an auditory target (human or robotic voice) after which subjects need to respond with a key press.

Similar to Experiment 1, there were two types of trials: congruent trials and incongruent trials. In congruent trials (80% of total trials), the category of the visual cue matched the category of the auditory stimulus (e.g. human image and human voice, or a robot image and robotic voice). In incongruent trials, the category of the visual cue did not match the category of the auditory target (e.g. human appearance and robotic voice, or robotic appearance and human voice, see Figure 5). The total number of trials was the same with Experiment 1.

Figure 5. There are two types of trials in Experiment 2. A. Congruent trials in which the category of the visual cue and the auditory target match (e.g. human appearance (Human) and human voice, or robotic appearance (Android) and robotic voice), B. Incongruent trials in which the category of the visual cue and the auditory target do not match (e.g. human appearance (Human) and robotic voice, or robotic appearance (Android) and human voice).

Statistical Analysis

We conducted separate ANOVAs for Experiment 1 and Experiment 2, and an additional ANOVA to compare the results of Experiment 1 and Experiment 2.

Experiment 1: We conducted 2 (Congruency: Congruent, Incongruent) x 2 (Visual Cue: Human, Robot) repeated measures ANOVA to investigate the effects of congruency and visual cue (agent) on reaction times and accuracy.

Experiment 2: We conducted 2 (Congruency: Congruent, Incongruent) x 2 (Visual Cue: Human, Android) repeated measures ANOVA to investigate the effects of congruency and visual cue (agent) on reaction times and accuracy.

Comparison of Experiment 1 and Experiment 2: We conducted 2 (Congruency: Congruent, Incongruent) x 3 (Visual Cue: Human, Android, Robot) to investigate whether the congruency, the human-likeness of the agent, or their interaction affect reaction times or accuracy.

Results

Experiment 1 (Human, Robot)

Reaction Times:

We found a main effect of congruency on reaction times ($F(1,29) = 58.79, p < .05, \eta^2 = .55$). Subjects responded to auditory targets significantly faster in congruent trials (when the category of the auditory target matched to the visual cue category) (Mean = 1.28 sec, SD = 0.15) than incongruent trials (when the category of the auditory target did not match to the visual cue category) (Mean = 1.47 sec, SD = 0.16). We also found a main effect of agent (visual cue) on reaction times ($F(1,29) = 10.48, p < .05, \eta^2 = .04$). Subjects were significantly faster when the visual cue was Human (Mean = 1.35 sec, SD = 0.03) than it was Robot (Mean = 1.40 sec, SD = 0.03). There was no interaction between the congruency and the visual cue ($F(1,29) = 0.097, p = 0.76$).

We conducted pairwise t-tests between congruent and incongruent conditions for each visual cue category (Human and Robot) separately. When the visual cue category was Robot, subjects performed significantly faster in congruent trials (Mean = 1.30 sec, SD = 0.18) than

incongruent trials (Mean = 1.49 sec, SD = 0.17) ($t(29) = -7.23$, $p < .05$). Similarly, when the visual cue category was Human, subjects performed significantly faster in congruent (Mean = 1.26 sec, SD = 0.14) than incongruent conditions (Mean = 1.44 sec, SD = 0.16) ($t(29) = -7.22$, $p < .05$).

Accuracy:

There was a main effect of congruency on accuracy scores ($F(1,29) = 63.48$, $p < .001$, $\eta^2 = .68$). Subjects responded to auditory targets significantly more accurately in congruent trials (when the category of the auditory target matched to the visual cue category) (Mean = 88.06%, SD = 10.60) than incongruent trials (when the category of the auditory target did not match to the visual cue category) (Mean = 71.04%, SD = 16.47). However, there was no significant effect of visual cue on accuracy ($F(1,29) = 0.082$, $p = 0.78$). We did not find an interaction between congruency and visual cue, either ($F(1,29) = 0.22$, $p = 0.64$).

We conducted pairwise t-tests between congruent and incongruent conditions for each visual cue category (Human and Robot) separately for accuracy scores. Participants performed significantly more accurately in congruent trials (Mean = 88.54%, SD = 10.68) than incongruent trials (Mean = 71.08%, SD = 17.24) ($t(29) = 7.40$, $p < .05$) when the visual cue was Human. We also found that when the visual cue was Robot, subjects performed significantly more accurately in congruent trials (Mean = 87.58%, SD = 11.78) than incongruent trials (Mean = 71%, SD = 18.50) ($t(29) = 7.22$, $p < .05$).

Figure 6. Reaction Times (RT) and Accuracy (%) results of Experiment 1. Error bars show the standard error of the mean (SEM).

Experiment 2 (Human, Android)

Reaction Times:

We found a main effect of congruency on reaction times ($F(1,29) = 54.65$, $p < .001$, $\eta^2 = 0.56$). Subjects responded to auditory targets significantly faster in congruent trials (when the category of the auditory target matched to the visual cue category) (Mean = 1.27 sec, SD = 0.16) than incongruent trials (when the category of the auditory target did not match to the visual cue category) (Mean = 1.47 sec, SD = 0.16). We also found a main effect of visual cue on reaction times ($F(1,29) = 38.18$, $p < .001$, $\eta^2 = 0.04$). Subjects were significantly faster when the visual cue was Human (Mean = 1.34 sec, SD = 0.03) than it was Android (Mean = 1.40 sec, SD = 0.03). There was no interaction between the congruency and the visual cue ($F(1,29) = 0.90$, $p = 0.35$).

We conducted pairwise t-tests between congruent and incongruent conditions for each visual cue category (Human and Android) separately. When the visual cue category was Android, subjects performed significantly faster in congruent trials (Mean = 1.30 sec, SD = 0.17) than incongruent trials (Mean = 1.50 sec, SD = 0.16) ($t(29) = -6.94$, $p < .05$). Similarly, when the visual

cue category was Human, subjects performed significantly faster in congruent (Mean = 1.26 sec, SD = 0.16) than incongruent conditions (Mean = 1.43 sec, SD = 0.18) ($t(29) = -6.49, p < .05$).

Accuracy:

There was a main effect of congruency on accuracy scores ($F(1,29) = 42.54, p < .001, \eta^2 = .60$). Subjects responded to auditory targets significantly more accurately in congruent trials (Mean = 90.23, SD = 8.19) than incongruent trials (Mean = 71.29, SD = 20.58). However, there was no effect of visual cue on accuracy ($F(1,29) = 0.30, p = 0.59$). We also did not find an interaction between congruency and visual cue ($F(1,29) = 0.06, p = 0.81$).

We conducted pairwise t-tests between congruent and incongruent conditions for each visual cue category (Human and Android) separately for accuracy scores. Participants performed significantly more accurately in congruent trials (Mean = 90.52 %, SD = 8.11) than incongruent trials (Mean = 71.92 %, SD = 21.03) ($t(29) = 6.00, p < .05$) when the visual cue was Human. We also found that when the visual cue was Android, subjects performed significantly more accurate in congruent trials (Mean = 89.94 %, SD = 9.12) than incongruent trials (Mean = 70.83, SD = 22.33) ($t(29) = 6.29, p < .05$).

Figure 7. Reaction Times (RT) and Accuracy (%) results of Experiment 2. Error bars show the standard error of the mean (SEM).

The human-likeness dimension: The comparison of Experiment 1 and Experiment 2

In addition to the main analyses reported above, we explored whether the human-likeness of the agent in the spectrum of Human-Android-Robot affected the reaction times or accuracy. To this end, we compared the reaction times of Experiment 1 and Experiment 2. Since the Human agent existed in both experiments, we did two separate ANOVAs.

Reaction Times:

First we ran a 2 (Congruency: Congruent, Incongruent) x 3 (Visual Cue: Human, Android, Robot) ANOVA using the Human and Robot RTs from Experiment 1, and Android RTs from Experiment 2. We found a main effect of congruency ($F(1,29) = 68.98, p < .05, \eta^2 = 0.50$) and of visual cue ($F(1,29) = 4.26, p < .05, \eta^2 = 0.03$). Pair-wise comparisons (Bonferroni-corrected) between the three agents (visual cues) show that participants were faster when the visual cue was Human as compared to Android ($t = -2.512, p = 0.044$) or Robot ($t = -2.548, p < .05$). They responded similarly when the visual cue was Robot or Android ($t = -0.036, p = 1.0$). There was no interaction between congruency and visual cue ($F(1,29) = 0.26, p = .07$).

We ran a second 2 (Congruency: Congruent, Incongruent) x 3 (Agent: Human, Android, Robot) ANOVA using the Human and Android RTs from Experiment 2, and Robot RTs from Experiment 1. We found a main effect of congruency ($F(1,29) = 67.86, p < .05, \eta^2 = 0.47$), and of visual cue ($F(1,29) = 4.36, p < .05, \eta^2 = 0.03$). There was not an interaction between congruency and visual cue ($F(1,29) = 0.36, p = .70$). Pairwise comparisons (Bonferroni-corrected) between the three agents (visual cues) show that participants were faster when the visual cue was Human as compared to Android ($t = -2.540, p < .05$) or Robot ($t = -2.573, p < .05$). They responded similarly when the visual cue was Robot or Android ($t = -0.033, p = 1.0$).

Accuracy:

For completeness, we also ran two 2 (Congruency: Congruent, Incongruent) x 3 (Agent: Human, Android, Robot) ANOVAs combining the scores of Experiment 1 and Experiment 2. In

the first ANOVA, we combined the Human and Robot scores in Experiment 1 and Android scores in Experiment 2. We found a main effect of congruency ($F(1,29) = 70.44$, $p < .05$, $\eta^2 = 0.65$). However, there was no significant effect of the visual cue ($F(1,29) = 0.19$, $p = 0.83$). We also did not find an interaction between congruency and visual cue ($F(1,29) = 0.49$, $p = 0.62$).

In the second ANOVA, we combined the Human and Android accuracy scores in Experiment 2 and Robot scores in Experiment 1. Our results show that there was a main effect of congruency ($F(1,29) = 54.52$, $p < .05$, $\eta^2 = 0.65$). However, we did not have a significant effect of visual cue ($F(1,29) = 0.66$, $p = 0.52$). We also did not find an interaction between congruency and visual cue ($F(1,29) = 0.59$, $p = 0.56$).

Discussion

We investigated whether expectations about artificial agents affect our perception. To this end, we used a well-known prediction paradigm from cognitive psychology in human-robot interaction context. We hypothesized that people would get faster in judging how an agent sounds like (human-like or robotic) if it was preceded by a congruent visual cue (e.g. a robotic picture for a robotic voice) than an incongruent visual cue (e.g. a human-like picture for a robotic voice).

Our results suggest that people form expectations about how an agent sounds based on the appearance of the agent. For instance, if the visual cue is a robot, people expect that it would sound robotic, as demonstrated by shorter reaction times and more accurate responses when the appearance and voice were congruent than when they were incongruent. This was true whether the robot has a more human-like appearance or less human-like. These results are consistent with previous work that suggests that predictive processes underlie our perception (Friston, 2010; Clark, 2013; Kok et al., 2013; Kok and de Lange, 2015; de Lange et al., 2018) including humans and robots. In other words, it seems that we can extend our predictive capabilities to perceive artificial agents, and just like our interaction with other humans, our expectations can affect how we perceive non-human agents.

Although there have been studies that examined the congruence of appearance and voice in perception of robots, most of these studies use subjective measures in characterizing people's experience with these agents (Mitchell et al., 2011; Hastie et al., 2017; Cabral et al., 2017; Stein and Ohler, 2018; Tsiourti et al., 2019; Mara et al., 2020). We extend this work by characterizing perception with more objective measures such as reaction time and accuracy. One advantage of this approach is that it has enabled us to make more direct links with the perception literature in cognitive sciences. Consistent with previous work on predictive processing in perception of simple or complex object stimuli (Kok et al., 2013; Kok and de Lange, 2015; de Lange et al., 2018), we found that reaction times get longer, and accuracy scores get lower when we encounter stimuli that we do not expect. This in turn suggests that our expectations affect how we perceive non-human agents as they do with other object categories.

What is the importance of studying how our expectations affect our perception of robots beyond improving our understanding of predictive processing in human cognition? Are there any practical implications? Previous work suggests that an important criterion in the design of robots is to avoid the uncanny valley (Mori, 1970). Uncanny valley is characterized as a non-linear relationship between the degree of human-likeness an artificial agent possesses and humans' reaction to it: It has been shown that people show increasingly positive responses as an artificial agent gets more human-like up to a point where the resemblance of a real human induces completely opposite, negative responses (MacDorman et al., 2009). One prominent explanation for the uncanny valley is that artificial agents which are almost human-like lead people to think that they possess human norms, so they expect them to look and act completely human, but because of their imperfections in one way or the other, they violate people's expectations (Saygin et al., 2012; Urgen et al., 2018). The implication of this explanation is that roboticists should design artificial agents in such a way that they do not violate people's expectations, because otherwise people may find them eerie and may not want to interact with them (Yamamoto et al., 2009; Cheetham et al., 2013; Mitchell et al., 2012; Tinwell et al., 2010; 2015; MacDorman and

Chattopadhyay, 2016; Lee, 2010). So, in this context, what we expect from robots and in what ways they may violate our expectations become an important research question. Appearance and voice examined in the present study as well as in some other work (Mitchell et al., 2011; Tinwell et al., 2015) are only two features among many, for which we seek a match in agent perception. Future work could investigate what features of artificial agents make us form expectations, how we do that, and under what conditions these expectations are violated.

Another implication of the present study for future research is about individual differences in perception of robots. An interesting finding of our study is that people are overall faster when the visual cue that triggers expectations is a human than a robot, regardless of how human-like the robot is. One potential explanation of this finding is that people are much more familiar with other humans than robots, and this familiarity might have facilitated how expectations influence perception. On the other hand, recent research suggests that people may differ in how they respond to artificial agents (Macdorman and Entezari, 2015), consistent with other work in cognitive sciences (Kanai and Rees, 2011). One important question in the context of the present study is whether there are individual differences in forming expectations about robots. Note that expectations are formed based on previous experiences. Thus, one could predict that familiarity with robots (how much you know about them) can affect what we expect from them. For instance, an engineer in Japan who is heavily exposed to robots may not be surprised by a metallic-looking robot speaking with a humanlike voice as much as a person who has never interacted with a robot. Similar concerns may apply when we consider different generations. For instance, children who are born in the last decade in the technology era may have different expectations from robots compared to elderly. Future work should investigate how familiarity with robots can affect our prediction abilities. This will enable the design of customized robots for different end users.

The present study also sets as a good example about how the collaboration between human-robot interaction and cognitive sciences can be fruitful and useful for both sides. Our study not only suggests possible principles for robot design but also shows how fundamental cognitive

mechanisms such as prediction can generalize to agents that we have not evolved with over many generations. As such, our study shows that artificial agents such as robots can be great experimental tools for cognitive science to improve our understanding of the human mind.

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