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IEEE PROCS

# Cognitive Impact of Social Robots

## *How Anthropomorphism Boosts Performance*

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By Nicolas Spatola, Sophie Monceau, and Ludovic Ferrand

**E**vidence shows that a robotic agent in the presence of a human can affect selective attention mechanisms in that human in the same way the presence of a fellow human can. *<AU: Please check whether the preceding edited sentence conveys the intended meaning.>* However, it's uncertain whether this process stems from anthropomorphism attribution. We investigated this issue using a selective attention task in a social-presence paradigm. One group of participants performed the so-called Eriksen Flanker task (EFT) in the presence of a robot after a verbal social interaction (i.e., social-robot condition), while the other group did the same with a robot that the participants only described (i.e., nonsocial-robot condition). Results showed that, after social interaction, the robot was perceived as having human traits (according to the humanization and anthropomorphism scale). Furthermore, we found a social-presence effect (i.e., an improvement in selective attention performance) only in the presence of the social robot but not in the presence of the nonsocial one. Finally, this latter effect was mediated by anthropomorphism

attributions. Our results suggest that the influence of the robot's presence is sociocognitive in nature and that anthropomorphism has a role in the robot-presence effect.

### **Applying Research on Human Presence and Attention**

*<AU: Please check that the edited section heading is appropriate.>*

Humanoid robots will likely take on increasingly important roles the lives of millions of people worldwide [1], [2]. While tremendous progress has been made in robotics science, the influence that these new humanoid robots may have on human cognition itself remains poorly understood. Evidence indicates [3]–[6] that the presence of a humanoid robot can lead to effects similar to those caused by human presence in terms of feelings [7] and task performance [3], [4]. However, this pioneering research has overlooked both the interaction between attentional processes and the anthropomorphic inferences that may be involved in the influence of a robotic presence. Here, we take advantage of research on human presence and attention and argue that the presence of humanoid robots may, even when the robots are passive, affect attentional processes, at least when the robot present is anthropomorphized to some extent.

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## **Social Presence and Social-Robot Presence Effects**

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A century of research in experimental social psychology has shown a tendency for humans to perform differently on a myriad of motor and cognitive tasks when in the presence of conspecifics—other members of the same species—than they do when they are alone. Zajonc [8] was the first to notice that the presence of observers or coactors typically enhances performance on easy or well-learned tasks and impairs performance on difficult or poorly learned tasks. Taking this idea further, Baron's distraction/conflict theory suggested an integrative attentional view of this so-called social facilitation/inhibition (SFI) effect [9]. The key idea was that social presence, when it distracts or diverts attention from the focal task, can create attentional conflict, specifically a form of response conflict concerning the appropriate attentional response (to pay attention to the focal task or to the person present). This conflict, in turn, may result in cognitive overload and, ultimately, restrict the attentional focus.

Attentional focusing may produce different effects. It may, on the one hand, activate dominant responses and improve performance. Because fewer cognitive resources are available, peripheral stimuli are screened out when the task is simple or requires attention to fewer central cues. However, attentional focusing might, on the other hand, impair performance by causing the neglect of certain crucial stimuli when the task is more complex or demands attention to a wide range of cues. <AU: Please check whether the preceding edited paragraph conveys the intended meaning.>

According to the Ethopoeia concept [10], automatic social reactions are triggered by situations that include social cues, which need not all originate from other humans [11], [12]. This concept also seems to apply to human-robot interactions (HRIs) [3], [5], [7], [10], [13]. For example, it has been shown that the modalities of interaction might directly affect how humans consider artificial social agents in response to the same robot [3], [5], [6].

For instance, a recent study [5] showed that a robot acting positively with participants (e.g., with empathy and consideration) during a question/answer paradigm produced less SFI than a robot acting negatively (e.g., with contempt and a lack of empathy). In the presence of a "bad" robot, participants tended to improve their selective attention performances (i.e., the ability to select the pertinent information in a task or a context and to ignore the nonrelevant information) on the Stroop task (in which individuals must identify the color in which a word is printed, while ignoring the word itself). No such improvement was observed in the presence of the "good" robot. As has also been found in human-human studies [14], [15], the presence of a robot seems, under certain circumstances, to improve the selectivity of attention to relevant information at the expense of competing cues in easy tasks [14]. Indeed, in Spatola et al.'s experiment, the presence of a bad social robot had the same impact on selective attention

performance as the presence of a human [14]. The authors suggested that this could have been due either to the unexpected activation of behavior from the attribution of anthropomorphic traits (i.e., the attribution of human characteristics to a nonhuman) [16] or to the perceived evaluative threat associated with the presence of an unpleasant robot [17]. However, while Spatola et al.'s study was informative, robots designed to live with us are not intended to appear threatening. Nevertheless, their impact on attentional mechanisms and behavior in general may actually depend to a great extent on what people come to believe (anthropomorphic inferences) about them. Subsequent research has shown that SFI effects may occur following a previous social interaction with a robot. This is due to the emergence of anthropomorphization processes triggered by the situation [6]. These findings run counter to a purely mechanistic approach, which reduces the effects of a robot's presence to the physical, visual, or acoustic distraction by an object, sometimes affecting human performance [9], and to the role of anthropomorphism. <AU: Please check whether the preceding edited paragraph conveys the intended meaning.>

However, because of the design used, Spatola et al.'s [5], [6] research could not specify the exact role of anthropomorphic inferences in the robot SFI on cognitive performance, and the nature of the anthropomorphic mediator of SFI effects remains unclear. Indeed, anthropomorphism is a complex concept that brings together various psychological processes, such as social categorization or the modulation of the conceptual distance between humans and robots. Finally, this research indicates that the presence of a social robot can boost attentional focusing even when this process requires the deployment of inhibitory control. However, this conclusion is limited solely to the task used in the study in question, namely the Stroop task.

Regarding the incentive to introduce robots in various environments, such as schools [18], it seems of prime importance to gain a thorough understanding of the impact of robot presence on human cognitive processes. One of the basic processes for learning is the selective attention process that helps filter out incidental, irrelevant information and focus on the information and stimuli that demand attention. Here, we intended to compare the SFI-mediating role of two major psychosocial mechanisms involved in interpersonal perception and behavior in a new attentional control task, the EFT, which measures selective attention performances. <AU: Please check that change from "Flanker task" to "EFT" is acceptable here and subsequently.> We therefore focused our research on the following questions:

- 1) Will robot SFI be found in another gold-standard task of response inhibition measuring selective attention?
- 2) Are SFI effects involving robots due to the use of universal social perceptual dimensions that drive social categorization (i.e., warmth and competence) by the observer [19]?
- 3) Are SFI effects involving robots also based on the attribution of concepts uniquely inherent to humans [20] and thus responsive to a modulation of the conceptual

distance between the robot and the representation of what humans are?

4) Are these processes mutually exclusive?

### **The EFT**

To generalize the robot SFI, we used the EFT [21], [22]. The EFT requires participants to judge the direction of the central cue in multicomponent stimuli. The task comprised congruent stimuli (e.g., »») and incongruent stimuli (e.g., «<») used to assess the ability to suppress information irrelevant for the task to be performed. Response times (RTs) are usually longer on incongruent than on congruent trials because of the incompatibility between the peripheral items and the central cue (i.e., the target). On incongruent trials, the interference caused by contradictory and/or irrelevant information requires a supplementary inhibition process, which is not present on congruent trials. Thus, the EFT specifically makes it possible to measure selective attention performance. As in the Stroop task, the response inhibition processes involved in the EFT are sensitive to the social nature of the context and the presence of other fellow creatures [22], [23].

### **The Perception of Social Robots**

The computers-are-social-actors theory [24] posits that people may understand and relate to machines in a way similar to the way they understand and relate to their fellow creatures. Humans do indeed tend to apply the same social scripts (specifying actions to be produced in various social situations [25], such as HRIs or human-human interactions [10]). This tendency may be strengthened by the physical presence of the artificial agent and its humanoid shape, as this shape provides more social cues to the observer [26]–[29].

Interestingly, this process may result in two nonexclusive sociocognitive phenomena: 1) the use of universal dimensions of social perception to apply social categorizations to artificial agents [30], [31] and 2) the change in the intrinsic representation of robots as a modulation of the conceptual human-robot distance [6], [20]. Both processes are related not only to how people perceive and consider others but also to how they behave in the presence of others [32]–[34].

### **Universal Dimensions of Social Perception to Characterize Artificial Agents**

<AU: Please check that the edited section heading is appropriate.>

According to Fiske, Cuddy, and Glick [19], [35], most interpersonal impressions are distributed along two main dimensions: warmth (e.g., sincerity, trustworthiness, morality) and competence (e.g., ambition, confidence). The warmth dimension predicts active behaviors, such as helping (high warmth) or attacking (low warmth). The competence dimension predicts passive behaviors, such as association (high competence) or neglect (low competence). The model is based on the notion that people, when interacting with an individual, will assess that individual's intent to either help or harm (i.e., warmth dimension) and the individual's competence/capacity

to act accordingly (i.e., competence dimension). <AU: Please check whether the preceding edited sentence conveys the intended meaning.> The results of this evaluation will trigger a social categorization process, whereby people are classified into groups based on similar characteristics. For example, members of social groups stereotyped as warm and competent are perceived much more positively than members of social groups stereotyped as cold and incompetent. Previous research indicates that social categorization processes underlying the perception of persons can be generalized to robots [31], [36]. Inspired by Fiske et al.'s model, Carpinella et al. have proposed a questionnaire to assess these dimensions of social evaluation with regard to robots [30]. We used this tool to evaluate the scope of the mediating role of the warmth and competence dimensions in robot SFI.

### **The Change in the Intrinsic Representation of Robots**

The theory of dehumanization describes a disposition toward others in which the observer deprives the other of social or fundamental human characteristics. The dehumanization process, theorized by Haslam [20], refers to perceiving or treating people as less than human. <AU: Please check whether the preceding edited sentence conveys the intended meaning.> This process consists of two bidimensional negative/positive constructs illustrating the human essence: 1) animalistic dehumanization opposed to human uniqueness (e.g., amorality/moral sensibility), which distinguishes humans from other animals on typical socially learned characteristics, and 2) mechanistic dehumanization opposed to human nature (e.g., rigidity/cognitive openness), which represents fundamental characteristics of human beings and the gap between machines and humans. Interestingly, these dimensions echo the warmth/competence concepts. However, the dehumanization process is based on a modulation of the distance between the representation of what defines the concept of *human* and the representation of the other [34], [37], [38], rather than on a stereotyping process [39]. Harris and colleagues suggested that dehumanization occurs due to the decrease of neural activity toward the target [40]. Interestingly, this difference in neural activity is also observed in the comparison between human-human interactions and HRIs [41], [42]. This idea is supported by functional magnetic resonance imaging results showing that HRI is underpinned by human-human neurosocial mechanisms [42]–[44].

Regarding HRI, this process seems to be both bottom-up and top-down. First, perception (i.e., a bottom-up process) activates a motor resonance process. By providing a motor representation of the observed action through which the observer's motor system enters a state of direct resonance with that of the agent [45]–[47], motor resonance makes it possible to directly and immediately understand an action performed by others. In the same way that we cannot refrain from recognizing a face or a word when we perceive it, we cannot help but represent in motor terms the actions we perceive. During interactions with humans, the information that leads to this

activity is integrated automatically [48], [49] and is resistant to modulation by context [50], [51]. This system could be used to anticipate other people's actions [52]. In the case of robots, this automatic need to anticipate is still present [53].

However, the resonance would naturally be weaker and more context-dependent [54]. The reason could lie in the fact that it is more difficult to match the representation of a specific human action with the robot's actual action than it is to match it with another human's actual action [55]. If the context requires the system to interpret the movements of the robot in terms of human characteristics, then the system could act more forcefully to transform a weak bottom-up signal into a valid representation at the level of motor resonance by using top-down inferences concerning robots (i.e., social scripts, anthropomorphic inferences) [53], [56]. Due to these bottom-up/top-down processes, robots could trigger the same effect as humans do [3], [5] simply by being present and could, for example, activate "humanization" processes (i.e., attributing to them intentions, emotions, or mental states comparable to those of humans) [44], [57]–[59]. In other words, the process might represent the opposite of dehumanization. Furthermore, because in HRI this process is sensitive to contextual pressures, a particular robot will not be considered to be the same in different contexts (e.g., social versus nonsocial context) and will produce different sociocognitive effects [6].

## The Present Study

### Objective

In this study, our aim was to evaluate the mediating role of the universal social perceptual dimensions of warmth and competence on SFI as well as the role of the intrinsic representation of robots activated within a social HRI compared to a nonsocial HRI. To do so, we used a verbal social-interaction paradigm with a simple humanoid robot without any facial expression to control for emotional priming effects. Verbal social HRI is thought to increase the likelihood of human characteristics being attributed to the robot because of the activation of automatic social scripts that we use in human–human interactions [10]. This design should therefore maximize anthropomorphic inferences in only one of two robotic conditions [6]. After the HRI induction, the participants performed a selective attention task in the passive presence of the robot.

### Hypotheses

First, we hypothesized that, after a social HRI, robots should trigger the same SFI on selective attention as humans do; that is to say that robots should prompt an improvement in response inhibition performances [3], [5], [14], [15]. Because the inhibition process is similar in both the Stroop task and the EFT, we hypothesized that, in the presence of the social robot, participants should produce better performances than in the presence of the nonsocial robot. The presence of the social robot should result in the attentional focus being narrowed to the central cue at the expense of the peripheral cues, thereby reducing the response conflict [6], [9].

Second, we expected to observe an increased level of attribution on the universal dimensions of both warmth and competence. We also expected an increase in the intrinsic representation of robots on essential human dimensions. More specifically, we expected the robot in the social-robot condition to be attributed a higher level of warmth due to the social nature of the experience, as well as to be attributed more competence due to the more complex HRI in the social condition compared to the simple description required in the nonsocial condition. Regarding the intrinsic representation of robots, we expected the participants to perceive the robots as sharing more human-nature traits in the social than in the nonsocial condition.

Third, the SFI effect in the social condition should be mediated by the inferences made about the robot. Indeed, according to previous research showing that social interaction promotes the attribution of human traits [6], [60], we hypothesized that the more highly the participants perceived the robot on the universal dimensions of warmth and competence used in social categorization, the more sensitive they should be to its passive presence, thus resulting in a higher SFI. The same phenomenon should occur as a function of the level of perceived shared human traits.

We conducted an exploratory analysis to compare the hypothetical mediation factor of SFI. The purpose was to identify the main determinant of this sociocognitive phenomenon.

## Method

### Participants

The participants were 80 French students at Université Clermont Auvergne [median age, 19.32 years; standard deviation (SD), 2.05; 68 females; 12 males] with normal or corrected-to-normal vision (27 in the alone condition, 27 in the nonsocial-robot condition, and 26 in the social-robot condition). Sample size was determined—as recommended by Tabachnick and Fidell [61]—on the basis of the desired power (0.80), alpha level (0.05), number of groups (three in the main analysis), and anticipated effect size based on human-presence effects (using between-subjects design) in a Stroop paradigm ( $\eta_p^2 = 0.40$ ; [23]). Using G\*Power 3.1 [62], the minimum required sample size was calculated as 66.

### Procedure

The participants performed the EFT twice (Session 1, Session 2). First (Session 1), all of the participants performed the task alone (the experimenter left the room). The first session was used as a control to ensure that the different groups performed equally on the EFT without any experimental induction. It also made it possible to ensure that all participants had comparable knowledge and skill with regard to the task. At the end of the first session, the participants were randomly assigned to one of the three conditions:

- 1) In the alone condition, they had to describe a picture of Central Park. This task was used as a distractor task to maintain the reliability of group comparisons at the level of intersession activities.



- 2) In the nonsocial-robot condition, they had to describe the design of the robot that the experimenter brought into the room.
- 3) In the social-robot condition, they were asked to interact verbally with the same robot in (unknown to them) a “Wizard of Oz paradigm” [63]. The robot was presented as a work in progress. The robot was the same in both the social and nonsocial conditions.

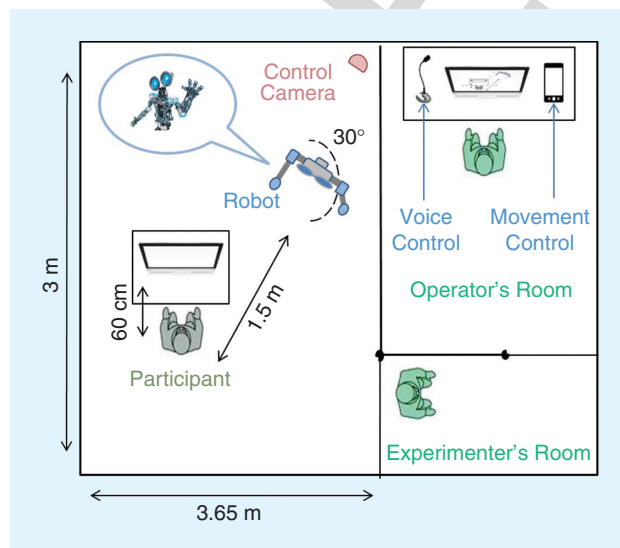
The social and nonsocial conditions had been pretested [6].  
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The participants were asked whether they agreed to describe or to interact with the robot, according to the experimental condition. They were told that the purpose of the study was to collect their impressions of the robot to improve it. The tasks took the same amount of time.

After a break, all of the participants performed the EFT again, either alone (as before) or in the presence of the robot. In the two robot-presence conditions, the robot was positioned in front of the participants and watched them for 60% of the time (for a similar procedure with human presence, see [14] and [15]). The interaction always followed the same preestablished script [see supplementary materials at Open Science Framework (OSF): <https://osf.io/kfvd8/>) (Figure 1).

### Wizard of Oz

A smartphone with a Bluetooth connection controlled the robot, a Meccanoid G15 KS. A Motorola Moto G 4G smartphone controlled the movements. <AU: Please check whether the preceding edited sentence conveys the intended meaning.> The operator produced the robot’s speech using a modified voice. The voice was designed using the Pixie voice module on Voxal from NCH Software. A hidden control camera was used to ensure correct control of movements and responses in the Wizard of Oz paradigm [5], [63].



**Figure 1.** A diagram showing the experimental setting.

### EFT

Each session (Sessions 1 and 2) consisted of 220 trials, i.e., 110 congruent (55 “<<<<” and 55 “>>>>”) and 110 incongruent (55 “<><>” and 55 “<<<<”) trials. The Flanker interference was computed by subtracting the RTs of congruent trials from the RTs of incongruent trials (in milliseconds). The higher the score, the less efficient was the selective attention performance.

Before the experimental trials in the first session, the participants responded to 20 samples to enable them to learn the response keys (“##<##”, “##>##”).

### Anthropomorphic Inferences

At the end of the experiment, the participants completed the Robotic Social Attribute Scale [30]. This scale makes it possible to evaluate robots on the dimensions of warmth (e.g., “emotional”), competence (e.g., “interactive”), and discomfort (i.e., “I find this robot scary”). This scale has been standardized to measure the social perception of robots based on their appearance. For each dimension, the participants had to indicate whether they thought the different characteristics fitted the presented robot (from 1, “does not fit at all,” to 5, “totally fits”).

The participants also completed the humanness scale based on Haslam’s dehumanization taxonomy [20], which consists of four dimensions: human uniqueness (e.g., moral sensibility), animalistic dehumanization (e.g., irrationality), human nature (e.g., interpersonal warmth), and mechanistic dehumanization (e.g., inertness). Once again, for each dimension, the participants rated (on a scale from 1 to 5) whether or not they would attribute the related characteristics to the robot present with them. For a similar use of these questionnaires, see [5].

We presented the scale at the end of the study to avoid any priming effect due to questionnaires. However, the anthropomorphic inferences in conditions with and without robot interaction had been evaluated in a pretest [6].

## Results

### Preliminary Analyses

The data from three participants were excluded from the analysis because of technical problems (i.e., robot disconnection, program crash). In addition, the data from participants with an accuracy rate lower than 70% were discarded because we could not be sure they performed the task conscientiously (seven participants). The results obtained from the remaining participants are summarized in Table 1. Errors occurred on 8.83% of the trials and were analyzed independently. Correct trials with RTs more than 2.5 SD above or below the mean in each condition and for each participant were considered outliers and removed from the RT analyses. These amounted to 771 of 26,805 trials (2.87% of the trials). This filtering procedure has the advantage of excluding extreme values without specifically affecting the data of any one condition or any one participant (raw data are available on OSF: <https://osf.io/kfvd8/>). The analyses were conducted using SPSS 24 and the mediation analyses using the Process plug-in.

**Table 1. Mean correct RTs (in milliseconds), standard errors (in parentheses), accuracy, and error rates as a function of the type of stimulus, Flanker session, and experimental condition.**

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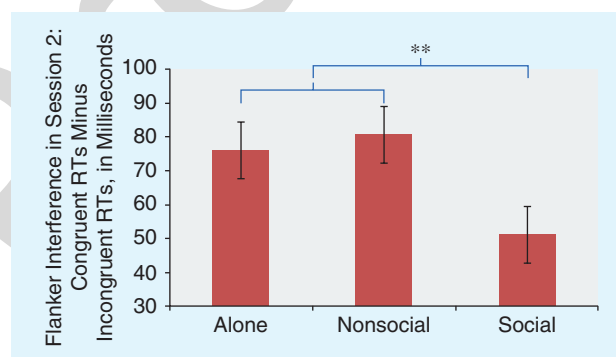
		Alone		Nonsocial Robot		Social Robot	
		Session 1	Session 2	Session 1	Session 2	Session 1	Session 2
Congruent	RT	246.61 (13.21)	220.36 (12.14)	275.72 (13.21)	229.22 (14.96)	247.72 (13.80)	231.72 (12.69)
	Accuracy	0.95 (0.01)	0.97 (0.01)	0.96 (0.01)	0.98 (0.01)	0.95 (0.01)	0.95 (0.01)
Incongruent	RT	351.86 (22.57)	296.83 (14.96)	368.05 (22.57)	310.11 (14.96)	338.85 (23.57)	287.76 (15.62)
	Accuracy	0.87 (0.03)	0.91 (0.02)	0.87 (0.01)	0.88 (0.02)	0.81 (0.03)	0.83 (0.02)
Interference	RT	87.25 (18.17)	76.47 (8.01)	92.34 (18.17)	80.98 (8.01)	91.12 (18.98)	51.04 (8.37)
	Results	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
		$\eta_p^2 = 0.26$	$\eta_p^2 = 0.58$	$\eta_p^2 = 0.28$	$\eta_p^2 = 0.60$	$\eta_p^2 = 0.26$	$\eta_p^2 = 0.36$
	Error rates	0.08 (0.03)	0.06 (0.02)	0.10 (0.03)	0.10 (0.02)	0.14 (0.03)	0.12 (0.02)
Results		$p = 0.007$	$p = 0.004$	$p = 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
		$\eta_p^2 = 0.11$	$\eta_p^2 = 0.12$	$\eta_p^2 = 0.16$	$\eta_p^2 = 0.23$	$\eta_p^2 = 0.26$	$\eta_p^2 = 0.30$

### Control Session

To ensure that all of the groups were comparable, we conducted two repeated-measures analyses of variance (ANOVAs) on both errors and RTs in Session 1, including the type of stimulus (congruent versus incongruent) as the within-subjects factor and the experimental condition as the between-subjects factor. Results showed no significant interaction between experimental condition and type of stimulus on either errors [ $F(2,67) = 1.25$ ,  $p = 0.293$ ,  $\eta_p^2 = 0.04$ ] or RTs [ $F(2,67) = 0.021$ ,  $p = 0.979$ ,  $\eta_p^2 < 0.01$ ]. However, the participants were more accurate on congruent trials than incongruent trials [ $F(1,67) = 41.84$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.38$ , 95% confidence interval (CI) (0.07; 0.14), **<AU: For consistency, the square brackets that included the CI values were changed to parentheses. Please confirm that this is acceptable.>**] and responses on congruent trials were faster than on incongruent trials [ $F(1,67) = 71.82$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.52$ , 95% CI (68.99; 111.49)].

### Experimental Session

We again conducted a repeated-measures ANOVA on Session 2 errors and RTs, including the type of stimulus (congruent versus incongruent) as the within-subjects factor and experimental conditions as the between-subjects factor. The results showed no interaction effect on errors between the type of stimulus and the experimental condition [ $F(2,67) = 1.65$ ,  $p = 0.201$ ,  $\eta_p^2 = 0.05$ ]. However, the main effect of the type of stimulus was significant [ $F(1,67) = 54.70$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.45$ , 95% CI (0.07; 0.12)]. The same effect was present on RTs [ $F(1,67) = 219.05$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.77$ , 95% CI (60.10; 78.84)]. Interestingly, we found a type of stimulus by experimental condition interaction on RTs [ $F(2,67) = 3.82$ ,  $p = 0.027$ ,  $\eta_p^2 = 0.10$ , 95% CI (0.07; 0.12)] (Figure 2). To test our hypothesis, we conducted a planned comparison analysis.



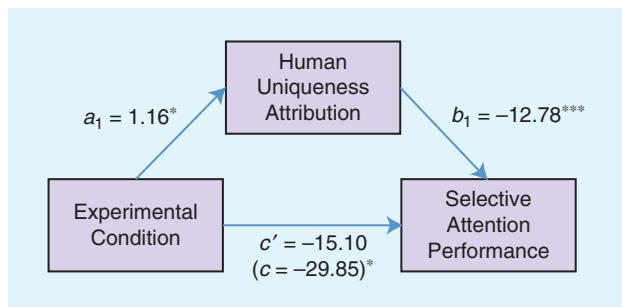
**Figure 2.** Eriksen Flanker interference (RTs on congruent trials minus RTs on incongruent trials) as a function of the experimental session (alone, nonsocial robot, social robot): the less positive the value, the better is the selective attention performance. Error bars represent one standard error. \*\*: **<AU: Please explain what \*\* indicates. Note that y-axis has been changed to “Flanker interference in Session 2: Congruent RTs minus incongruent RTs, in milliseconds”. Please confirm if this edit conveys the intended meaning.>**

This type of analysis reduces the risk of making a type-II error. Results showed that there was no significant difference between the alone and the nonsocial-robot experimental conditions [ $t(67) = 0.39$ ,  $p = 0.697$ ,  $\eta_p^2 < 0.01$ ], while the participants in the social-robot condition achieved higher selective attention performances than the average of those in the other two conditions [ $t(67) = 2.74$ ,  $p = 0.008$ ,  $\eta_p^2 = 0.14$ ]. This confirms our robot SFI effect hypothesis. The main effect of group **<AU: Please specify what is meant by “of group”>** on RTs (without taking account of the type of stimulus) was not significant [ $F(2,67) = 0.24$ ,  $p = 0.789$ ,  $\eta_p^2 = 0.01$ ].

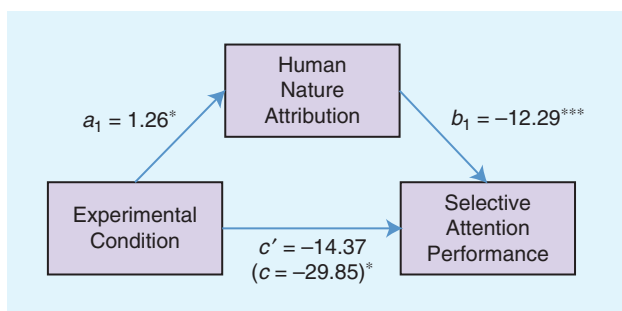
### Anthropomorphic and Humanization Attributions

If we consider the experimental conditions (social versus nonsocial), a multivariate ANOVA including the





**Figure 3.** A diagram showing the mediation of the robot-presence effect on standard selective attention performance by human-uniqueness inferences. \*. \*\*\*. **<AU: Please explain what \* and \*\*\* indicate in Figure 3.>**



**Figure 4.** A diagram showing mediation of the robot-presence effect on standard selective attention performance by human-nature inferences. \*. \*\*\*. **<AU: Please explain what \* and \*\*\* indicate in Figure 4.>**

anthropomorphism (i.e., warmth,  $\alpha = 0.82$ ; competence,  $\alpha = 0.88$ ; discomfort,  $\alpha = 0.77$ ) and humanization (i.e., human uniqueness,  $\alpha = 0.88$ ; animal dehumanization,  $\alpha = 0.60$ ; human nature,  $\alpha = 0.77$ ; mechanistic dehumanization,  $\alpha = 0.67$ ) attribution scores showed that the participants in the social-robot condition perceived the robot as having more uniquely human traits [e.g., maturity, logic;  $F(1, 44) = 4.33$ ,  $p = 0.043$ ,  $\eta_p^2 = 0.09$ , 95% CI (0.04; 2.29)], traits relating to human nature [e.g., cognitive openness;  $F(1, 44) = 6.70$ ,  $p = 0.013$ ,  $\eta_p^2 = 0.13$ , 95% CI (0.28; 2.24)], and warmth traits [e.g., happiness;  $F(1, 44) = 4.33$ ,  $p = 0.012$ ,  $\eta_p^2 = 0.13$ , 95% CI (0.27; 2.12)] than those in the nonsocial-robot condition. This finding validates our second hypothesis about the impact of social interaction on robot perception.

### Human Uniqueness

We conducted a first mediation analysis including experimental conditions, human-uniqueness attribution (mediator), and selective attention performance in the second session in a model [ $R^2 = 0.39$ ,  $F(2, 43) = 13.46$ ,  $p < 0.001$ ]. The results showed that the participants attributed more human-uniqueness traits to the robots in the social than in the nonsocial condition [ $(a_1) t(44) = 2.08$ ,  $p = 0.043$ , 95% CI (0.036; 2.29)]. When the effect of human-uniqueness attribution on selective attention performance was controlled for [ $(b_1)$

$t(44) = -4.39$ ,  $p < 0.001$ , 95% CI (-18.64; -6.91)], the direct effect of experimental conditions on selective attention performance [ $(c) t(44) = -2.33$ ,  $p = 0.025$ , 95% CI (-55.72; -3.98)] became nonsignificant [ $(c') t(44) = -1.33$ ,  $p = 0.192$ , 95% CI (-37.80; 7.80)]. This suggests that mediation took place. In sum, in the social-robot condition, participants attributed more human-uniqueness traits to the robot than they did in the nonsocial-robot condition. After the social interaction, the more uniquely human characteristics they perceived the robot possessing, the greater was the performance improvement generated by the presence of the robot [ $b = -0.33$ , 95% CI (-0.64; -0.01)] (Figure 3).

### Human Nature

The second mediation analysis differs only in that human-nature attribution replaces human-uniqueness attribution as a mediator in the model [ $R^2 = 0.30$ ,  $F(2, 43) = 9.33$ ,  $p < 0.001$ ]. In confirmation of our hypothesis, the analysis showed that the participants attributed more human-nature traits to the robot in the social HRI condition [ $(a_1) t(44) = 2.59$ ,  $p = 0.013$ , 95% CI (0.28; 2.24)]. When the effect of human-nature attribution on selective attention performance [ $(b_1) t(44) = -12.29$ ,  $p < 0.001$ , 95% CI (-19.47; -5.11)] was controlled for, the direct effect of experimental condition on selective attention performance [ $(c) t(44) = -2.33$ ,  $p = 0.025$ , 95% CI (-55.72; -3.98)] became nonsignificant [ $(c') t(44) = -1.17$ ,  $p = 0.250$ , 95% CI (-39.24; 10.50)], thus suggesting that mediation occurred. Once again, the participants in the social-robot condition attributed more human-uniqueness traits to the robot than those in the nonsocial-robot condition. After the social interaction, the more human-nature traits (e.g., cognitive openness) they perceived the robot possessing, the greater was the performance improvement brought about by the presence of the robot [ $b = -0.34$ , 95% CI (-0.69; -0.08)] (Figure 4).

### Warmth

The final analysis introduced the warmth dimension as a mediator in the model [ $R^2 = 0.19$ ,  $F(2, 43) = 5.11$ ,  $p < 0.01$ ]. As shown by the ANOVA, the participants attributed more warmth traits to the robot after the social HRI than after the nonsocial HRI [ $(a_1) t(44) = 2.61$ ,  $p = 0.012$ , 95% CI (0.27; 2.12)]. When the effect of warmth attribution on selective attention performance [ $(b_1) t(44) = -2.10$ ,  $p < 0.041$ , 95% CI (-16.78; -0.33)] was controlled for, the direct effect of the experimental conditions on selective attention performance [ $(c) t(44) = -2.33$ ,  $p = 0.025$ , 95% CI (-55.72; -3.98)] became nonsignificant [ $(c') t(44) = -1.48$ ,  $p = 0.147$ , 95% CI (-46.43; 7.17)], thus suggesting that mediation occurred. In sum, the participants in the social-robot condition attributed more human-uniqueness traits to the robot than those in the nonsocial-robot condition. After the social interaction, the more uniquely human characteristics they perceived the robot possessing, the greater was the performance improvement generated by the presence of the robot [ $b = -0.22$ , 95% CI (-0.50; -0.01)] (Figure 5).

## The Best Predictor of Performance Improvement

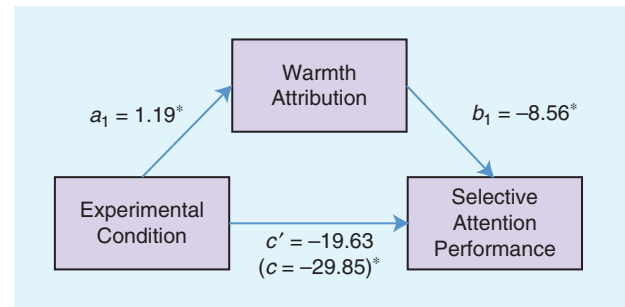
We conducted a regression analysis on selective attention performance in the second session, including the scores on the three anthropomorphism dimensions and the four humanization dimensions. This analysis makes it possible to evaluate the unitary effect of each variable to extract the best predictor, while controlling for collinearity. When all of the other dimensions were controlled for, the results showed that only the attribution of human-uniqueness traits had a significant predictive effect on selective attention performance [ $b = -0.63$ ,  $t(45) = -2.80$ ,  $p = 0.008$ ,  $\eta_p^2 = 0.17$ , 95% CI (-25.29; -4.07)]. The more uniquely human traits the participants considered the robot to possess, the better they performed in the second session. We also found a statistical trend toward a significant effect of discomfort attribution: the more the participants described the robot as having discomfort traits (e.g., awkward), the lower the interference due to incongruence in the EFT during the second session [ $b = -0.25$ ,  $t(45) = -1.75$ ,  $p = 0.089$ ,  $\eta_p^2 = 0.07$ , 95% CI (-23.75; 1.75)]. These results were confirmed by the mediation comparison analysis, including all dimensions as independent mediators in a global mediation model [ $R^2 = 0.47$ ,  $F(2, 43) = 4.17$ ,  $p < 0.01$ ]. Again, only mediation by human uniqueness was significant [ $b = -37$ , 95% CI (-0.50; -0.01)], thereby validating the third hypothesis concerning the modulation of the robot-human conceptual distance as a mediator of SFI effects.

## Discussion

In the future, robots are likely to be more common in the everyday human environment. It seems crucial to understand today how their presence may affect human cognitive processes. The aim of this study was to evaluate how the passive presence of a robot affects human cognitive performance. <AU: Please check whether the preceding edited sentence conveys the intended meaning.>

First, we demonstrated that social interaction changed how participants considered the robot in terms of human-uniqueness (e.g., cognitive openness), human-nature, and warmth traits compared to a simple description. This result confirmed that the nature of the HRI influences how humans represent the nearby robot [64]. It is important to note that social interaction only boosted positive attributions (i.e., more human-uniqueness, human-nature, and warmth traits), while negative attributions (i.e., animal-dehumanization, mechanistic-dehumanization, and discomfort traits) remained stable.

These results could point to two phenomena. First, negative attribution does not change because, unlike humans, robots seem to be considered objects. In contrast to a human being, who can be dehumanized, a robot cannot be deanthropomorphized. One can only assign new human constructs [65]–[67] or social traits [30] to the robot, as if this social agent were a “blank page.” However, it seems likely that this process applies only to new HRI. In the same way as for humans, it is possible that, once a robot has been anthropomorphized, subsequent HRI might modulate these inferences. However, the question of



**Figure 5.** A diagram showing mediation of the robot-presence effect on standard selective attention performance by warmth inferences. \*: . <AU: Please explain what \* indicates in Figure 5.>

whether long-term HRI might increase, stabilize, or reduce this type of anthropomorphism process remains unclear [68].

Second, these anthropomorphic inferences occur only in specific contexts that require such inferences to be made. The scientific literature shows that there are automatic neurosociocognitive perceptual processes, such as face recognition (automatically activated during simple perception, even with nonhumans) [69], [70]. In the case of HRI, it seems likely that the perception of and interaction with robots are based on such processes. However, this “hijacking” of human-human interactions, together with the automatic neurosocial processes they involve and that result from the social evolution of our species, is not enough to cause the attribution of social constructs [44]. In other words, the strength of bottom-up inputs is not enough in itself. To create anthropomorphic inferences, it is necessary for the context to reinforce these bottom-up inputs through top-down processes activated by the context (e.g., the type of HRI, the robot’s behavior). For example, in both experimental conditions in this study, the robot was perceived in the same way before the interaction. The robot was not seen as more “mechanical” in one condition than in the other as a function of the stability of the negative attributions. In other words, the robot started with a certain quantity of mechanical (e.g., superficial) and animal (e.g., amoral) traits, and this quantity remained stable, even after the experimental induction. However, we suggest that the activation of social scripts during the social interaction would have led to the attribution of a more anthropomorphic perception of the robot [7], [13], [71]. The reason could be that when we interact with creatures (even nonhumans), processes (e.g., mentalization) occur that allow us to attribute intentionality and mental activity to the other to understand and predict that other’s behavior [44], [72].

We found the same effect for the “warmth” dimension of the “warmth and competence” dyad, which is considered to represent universal dimensions of social perception [19]. This result is interesting in that it suggests that, when people spontaneously interpret their impressions of others, these two dimensions account for almost all of the variance ( $\approx 82\%$ ) [73]–[75]. Given the universal qualities of the warmth and competence dimensions, it might be asked why we found no such results for competence attribution. Warmth judgments are primary; that is to say, they are made before competence judgments.

In addition, warmth also carries more weight in affective and behavioral reactions. This also accounts for traits relating to dehumanization dimensions. For example, the attribution of morality traits from the human-uniqueness dimension (which is strongly correlated with the warmth dimension) determines approach-avoidance tendencies that require each to evaluate the other (i.e., positively or negatively) [76]. This information is more cognitively accessible and more predictive. Competence is related more to the modulation of impression (e.g., how positive or how negative). The fact that the HRI induction in our experiment lasted only three minutes suggests that the participants might have gained only a general impression of the robot. Further research should focus on the evolution of these attributes in long-term HRI as compared to human-human interaction.

Furthermore, according to our results, anthropomorphic attributions seem to mediate the effect of the presence of a social robot on selective-attention-performance improvement. Again, these results are in line with research on robots [43], intentional stance perception (i.e., the attribution of mental properties) [77], and the mentalization process (i.e., attribution of mental activity) [72]. In our experiment, after the social HRI, the robot could have been perceived by the participants as more conscious and similar to a fellow creature, thus resulting in a social-presence effect [14]. Indeed, anthropomorphic inferences are needed if the improvement in performance is to occur in the presence of the robot. Importantly, the passive presence of the nonsocial robot during the EFT in the second session did not influence performance compared to the control alone condition. Together, these findings run counter to a purely mechanistic, nonsocial approach that reduces the effects caused by the presence of humanoid robots on attention to the action of physical distraction or interference. Indeed, with regard to the role of top-down inference, anthropomorphism is at the center of the robot SFI processes when mechanistic distraction is controlled for.

There is evidence that, when a focal task demands attentional resources, perceptual (nonsocial) sources of distraction can induce a conflict between the need to pay attention to the focal task (i.e., the central stimulus in the EFT) and the interfering cues (i.e., the peripheral stimuli). This conflict may result in cognitive overload and, ultimately, restrict the use of the available cues (e.g., [9]). This restriction directs the available attentional resources toward the task that is to be performed at the expense of peripheral cues (e.g., by focusing more exclusively on the central stimulus than on peripheral interfering cues). According to this view, however, both experimental conditions should have elicited the same effects, which was not the case, even though the robot behaved in a similar way during the task. Considering the mediating role of anthropomorphic inferences, we can reasonably assume that the effects of social-robot presence on attention were indeed social in nature and cannot be trivialized or reduced to the action of any other nonsocial sources of distraction.

Finally, some limits have to be addressed. First, we specifically chose a mechanical humanoid robot to control for

anthropomorphic bottom-up inferences. It is therefore not yet possible to conclude that top-down reinforcement is necessary for all situations and for all types of robots. It is possible that a sufficiently human-like robot, with fluid movements, could stimulate anthropomorphic inferences on the basis of perceptual stimuli alone [55] as a condition to avoid the “uncanny valley” phenomenon (i.e., the theory that the more similar an android robot is to a human being, the more monstrous its imperfections seem to the human observer) [55], [78]–[80]. <AU: Please check whether the preceding edited sentence conveys the intended meaning.> The more human-like a robot is, the less interaction should be needed to stimulate anthropomorphism and thus social-presence effects [10], [26]. The relative compatibility between the advanced technological shape and the level of perceived capacities of a robot could also play an important role [42]. Second, the social-presence effect may degrade cognitive performances (i.e., social inhibition) when the number of attentional resources needed to complete the task and the number of attentional resources allocated to the other being present exceed an individual’s reserve of cognitive resources [9]. To fully assess whether the social-presence effect with robots is similar to that observed in the presence of humans, the same paradigm should be implemented with a complex task.

In conclusion, the fact that the presence of social robots can affect processes as fundamental as selective attention provides another reason to pay particular attention to the psychological, sociological, and philosophical impact of HRIs.

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BA



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**Humanoid robots will likely take on increasingly important roles the lives of millions of people worldwide**

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**According to the Ethopoeia concept, automatic social reactions are triggered by situations that include social cues, which need not all originate from other humans.**

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**Previous research indicates that social categorization processes underlying the perception of persons can be generalized to robots.**

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**Attentional focusing may produce different effects.**

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**The EFT requires participants to judge the direction of the central cue in multicomponent stimuli.**

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**The more human-like a robot is, the less interaction should be needed to stimulate anthropomorphism and thus social-presence effects.**

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