Individuals Expend More Effort to Compete Against Robots Than Humans After Observing Competitive Human–Robot Interactions

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Abstract. In everyday life, we often observe and learn from interactions between other individuals—so-called third-party encounters. As robots are poised to become an increasingly familiar presence in our daily lives, third-party encounters between other people and robots might offer a valuable approach to influence people's behaviors and attitudes towards robots. Here, we conducted an online experiment where participants ($n = 48$) watched videos of human—robot dyads interacting in a cooperative or competitive manner. Following this observation, we measured participants' behavior and attitudes towards the human and robotic agents. First, participants played a game with the agents to measure whether their behavior was affected by their observed encounters. Second, participants' attitudes toward the agents were measured before and after the game. We found that the third-party encounters influenced behavior during the game but not attitudes towards the observed agents. Participants showed more effort towards robots than towards humans, especially when the human and robot agents were framed as competitive in the observation phase. Our study suggests that people's behaviors towards robots can be shaped by the mere observation of third-party encounters between robots and other people.

Keywords: Human—robot interaction · Third-party encounters · Social robotics · Artificial agents · Social cognition · Cooperation · Competition

1 Introduction

We frequently observe interactions among others—so-called third-party encounters. These encounters influence people's attitudes towards the observed individuals and, if positive, can serve as an easily to implement and unthreatening tool to reduce prejudice towards minority groups, unfamiliar individuals and other outgroups [1–9]. Some

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evidence suggests that the effects of third-party encounters can equal or even surpass those brought about by direct contact [10]. Furthermore, these effects of vicarious contact have been shown to persist over time, and can even generalize beyond the observed agents [11, 12]. For example, it was found that children prefer the friends of people receiving positive non-verbal signals over friends of people receiving negative signals [12].

Third-party encounters hold great practical potential for improving human–robot interactions (HRIs). While robots become more prevalent in daily life [13], negative attitudes towards these machines persist [14]. Third-party encounters between humans and robots have been proposed as a possible tool to reduce people's negative attitudes towards robots by a number of different researchers [14–17]. For instance, Fraune and colleagues [16] showed that watching positive HRIs increased people's willingness to interact with robots.

So far, most research has focused on the impact of third-party encounters on observers' attitudes towards robots, with limited empirical evidence to date showing that these encounters can induce behavior change in the observer, specifically towards the observed agents [7]. Skinner and colleagues [12] found that observing an interaction between people can change some daily behaviors unspecific to the observed people. Yet, more research on behavioral change is essential to lay the foundations for robust HRI. For example, people who have negative attitudes towards robots have been also shown to behave more negatively towards robots during real-life interactions [17].

The aims of the current exploratory study were to replicate findings suggesting that attitudes towards robots can be changed by observing HRIs [1–9], and to investigate potential behavior change in observers [7] based on this observational manipulation. Specifically, we set out to examine whether observing videos of cooperative versus competitive HRIs influence how people perceive similar agents, as well as behave towards them. We conducted an online experiment where participants observed human–robot dyads acting cooperatively or competitively and assessed participants' attitude changes and motivation to engage with each observed agent in a simple, competitive game. Participants were led to believe that they were playing against an algorithm based on prerecorded behavior of the different agents. Based on the previous findings, we evaluated the following general expectations:

1. People should show a difference in motivation when playing the game with agents framed as cooperative versus competitive.
2. Participants should show differential preferences for cooperative vs. competitive agents. This is based on findings from Correia and colleagues [15], who showed that robots cooperating with the team were rated more positively than a robot following its own goal, regardless of the game result.

We further explored the extent to which opponent type influenced behaviors.

2 Methods

2.1 Data Accessibility Statement

Materials, data and code for all experiments are available on the OSF https://osf.io/uvy3b/. We report all measures in the study, all manipulations, any data exclusions and the sample size determination rule.

2.2 Participants

Forty-eight participants, of which 16 were female (M age = 26.2, SD = 6.8; sex of one participant remained unspecified) were recruited via Prolific (www.prolific.co). As a rule of thumb, we determined the sample size by multiplying the number of participants recruited in a comparable study by two. Specifically, we used the study by Walbrin and colleagues, Experiment 2 as reference (n = 23) [18]. The main experiment was described as watching videos of human and robotic agents followed by playing a game with these agents. To increase the believability of the online experimental setting, participants were told that they would play against algorithms based on these previously observed agents. Participants received £2.52 for their participation in the study (equivalent to £6.73/hour). To increase motivation, participants were told that the top 10% had a chance of receiving a bonus payment of £5. Inclusion criteria were an approval rate of 100% on the Prolific website and no participation in the validation and pilot studies prior to the main experiment (see below). Participants were naive to the goal of the study, most of them (87.5%) were unfamiliar with the robot used in the study and had little or no experience in interacting with robots in daily life (median on a scale from 1 (never) to 7 (daily) was 2 with an interquartile range of 1). The experiments were designed in PsychoPy3 and later uploaded to Pavlovia (https://pavlovia.org/; [19]) an online experiment platform. The whole experiment took approximately 20 min. Participants provided informed consent before the start of the experiment. The study procedure was approved by the Research Ethics Committee of the College of Science and Engineering at the University of Glasgow (protocol number: 300180301).

2.3 Experimental Design

We used a two-by-two (agent type: human or robot; agent intention: cooperative or competitive) within-subjects factorial design to examine the impact of agent type, agent intention, and the interaction between these two factors on participants' attitudes and behaviors towards the observed agents.

2.4 Stimuli

Participants watched 2 short videos (10 s) of a human and robot playing a bar game together, which served as a framing story to the main task. In these videos (Fig. 1A and 1B), a bar was located in the middle of the screen between two opposite goals, one in the upper and one in the lower part of the screen. The agents moved their arms either up or down, giving the impression that they controlled the movement of the bar.

In the cooperative condition, the human and robot appeared to work together to reach the same goal by moving their arm in the same direction simultaneously. In the competitive condition, both agents tried to reach opposite goals by moving their arms in opposite directions (Fig. 1B). The purpose of the videos was to frame each agent as either competitive or cooperative. Later in the experiment, participants engaged in a bar game similar to this one with one of the agents (either the cooperative robot, cooperative human, competitive robot or competitive human). The bar game looked almost identical to the one in the framing videos, but the participants could now actively move the bar upwards by pressing the space bar. Again, there were two goals, the upper one belonging to the agent. The videos were edited in DaVinci Resolve v15.3.1 1 [20]. The agents were filmed in front of a green screen, which was later removed and replaced by the bar game. Three validation studies (first validation: n = 20, second validation: n = 12, third validation: n = 40) were conducted in order to improve and select the most salient stimuli for the main experiment. The third validation study (containing the videos for the main experiment) showed that agents were consistently rated as either cooperative or competitive, on a slider from '1' as 'competitive' to '7' as 'cooperative' (cooperative human: M = 5.60, SD = 1.74, cooperative robot: M = 5.97, SD = 1.48, competitive human: M = 2.35, SD = 1.85, competitive robot: M = 2.17, SD = 1.75) (Fig. 2D). To avoid possible gender bias effects, we generated two different orders: order A in which the female human agent was the cooperative agent and the male was the competitive agent, and order B where the male human agent was the cooperative agent and the female the competitive agent. For all analyses, no differences were found between the two orders.

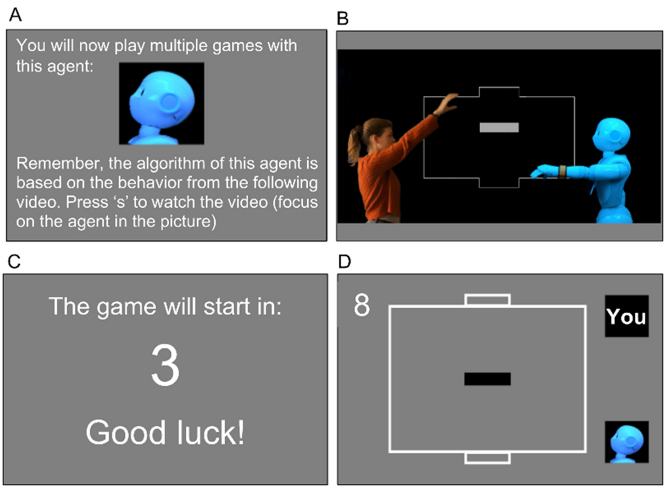

Fig. 1. Bar game design. (A) The bar game began with an agent's picture signifying participants' next opponent. (B) This was followed by a framing video. (C) Countdown to prepare the participant for the game. (D) The bar game lay-out.

2.5 Measures

To operationalize people's motivation to play against agents, we measured the number of space bar presses during the bar game. Participants played three games with each agent, and each game was at a different difficulty level (easy, medium or hard). Difficulty levels were manipulated to measure subtle differences in motivation and to increase believability of the bar game. The different difficulty levels were defined by: 1) the number of times the participant had to press the space bar before it could be moved upwards (from easy to hard respectively: 2, 4, 6), and 2) how many times the bar would move downwards towards the goal of the opponent agent (150, 100, 50). The resulting 12 games were played in a randomized order. A game ended either when ten seconds had passed or when one of the players reached one of the goals. After the game round ended, the score was presented and participants could see how many times they pressed the space bar, if they reached the goal, and if they received a penalty, as well as their total scores. Participants would get a penalty (-5 points) if they did not let go of the space bar (instead of pressing "space" repeatedly). Participants could receive one penalty per game, thus the maximum penalties per participant was 48. Penalties were low ($M = 1.79$, $SD = 3.75$). We interpreted more space presses as increased competitiveness and effort invested in the game. Measures of participants' attitudes towards agents involved three parts: First, participants' preference towards agents was measured before (pre-preference) and after (post-preference) the game by preferential ranking from "most preferable" to "least preferable" to play a game with. The pre- and post-measurements were implemented because we anticipated that an effect of the third-party encounters would be stronger in pre-preference (i.e., right after watching the framing videos) than in post-preference ratings (i.e., after playing the games where all agents played the role of a game opponent). Second, the perceived cooperativeness and socialness towards agents was determined by slider ratings from competitive to cooperative, and from individual to social. Last, participants' decisions of whether an agent was cooperative or competitive was acquired by using a two-alternative forced choice task.

2.6 Experimental Procedure

The main experiment consisted of four parts. First, participants observed two framing videos to learn the roles of each agent (cooperative or competitive agents). While watching the videos, they were instructed to pay attention specifically to one of the agents. One of the videos showed agents cooperating with each other, while the other showed two agents competing against each other. Each framing video was repeated twice for each agent. To check whether participants paid attention to the videos, they were asked whether the specified agent had reached the goal. Following the third-party encounters, participants ranked the agents from most to least preferable to play a game with. Next, participants played a bar game with each agent in a semi-randomized order. Before the game, participants read a cover story that suggested they were actually playing against an algorithm based on the observed agents' game behavior. Participants were told that the behaviors were modelled and created by using a deep neural network. The story was accompanied by an image of a schematic explanation of a deep neural network. The bar game (Fig. 1D) began with an agent's picture signifying this round's opponent (Fig. 1A).

To remind participants of the intention of the agent, the framing video was shown again (Fig. 1B). There was a countdown announcing the start of each game (Fig. 1C). After each game participants were shown their scores (Fig. 1E).

In the final part, each agent was rated on their socialness and cooperativeness levels. Ratings were placed at the end so that participants could form their own opinions throughout the experiment. Finally, we asked participants to describe the algorithm in their own words to check whether they believed the cover story. The free text responses showed that the words most used to describe the agents were ‘computer’ ($n = 51$), ‘man’ ($n = 22$), ‘woman’ ($n = 21$) and ‘robot’ ($n = 17$). It is not surprising that the agents are most often described as computers since a computer is often the layman’s interpretation of an algorithm.

2.7 Data Processing and Analysis

All data analyses were carried out in R v4.0.1 [21]. For the behavioral data of the numbers of space bar presses, we ran a linear mixed effects model with the lme4 package (v1.1.23) [22] to examine if participants’ game behaviors were influenced by agent type (human or robot) and agent intention (cooperative or competitive) while controlling the random individual differences (Prolific_id), trial differences (trial_number), and the random effects by game difficulty levels (difficulty_level). The model building started from the maximal random effect components [23], and we reduced the complexity, resulting in the following formula: numbers of presses ~ agent_type*agent_intention + (1 + agent_type |Prolific_id) + (1|trial_number) + (1|difficulty_level).

The analyses regarding participants’ attitudes toward each agent was done in three parts. First, participants’ ordinal ranking of the most preferable agent to the least preferable was analysed via a mixed effects ordinal regression model with the ordinal package (v2019.12.10) [24]. We tested the fixed effects of agent type (human or robot), agent intention (cooperative or competitive), and ranking timing (pre-game or post-game) on people’s ordinal preferences, while controlling the random effects of participants (Prolific_id) and the random order of the four agents introduced to each participant (present_order). The final model that converged was ranking ~ agent_type*agent_intention*rank_time + (1 + agent_type*agent_intention|Prolific_id) + (1 + agent_type*agent_intention|present_order).

Second, participants’ slider ratings of the agents’ cooperativeness and socialness were analysed via two linear mixed effects models respectively. For the cooperativeness model, agent type (human or robot) and agent intention (cooperative or competitive) were included as fixed effects, and the final random effect structure which led to model convergence involved: by-subject random intercepts, and random slopes for the effects of agent type and agent intention on subjects: cooperativeness_rating ~ agent_type* agent_intention + (1 + agent_type + agent_intention |Prolific_id). The socialness model was similarly designed, except that it included an additional random factor of order (order A or B): socialness_rating ~ agent_type* agent_intention + (1 + agent_type + agent_intention |Prolific_id) + (1|order).

Third, we analysed participants’ binomial forced choices on whether an agent was cooperative or competitive via a mixed effects logistic regression model with the “glmer” function in lme4 package (v1.1.23). We examined the fixed effects of agent type (human or robot) and agent intention (cooperative or competitive) on participants choices, while controlling by-subject random intercepts and random slopes for agent type on subjects: forced_choice ~ agent_type + agent_intention + (1 + agent_type|Prolific_id). All linear data were centred by the grand mean before model building. When conducting pairwise post-hoc tests, p-values were adjusted using Tukey's method. All analysis code can be accessed on our dedicated OSF page for this project: https://osf.io/uvy3b/.

3 Results

3.1 Behavioral Results (Bar Game)

The result of the mixed effects model showed a significant main effect of agent type ($\beta = 3.08$, 95% CI [0.78, 5.38], $p = .009$), and a significant interaction between agent type and agent intention ($\beta = -3.03$, 95% CI [−5.42, −0.65], $p = .013$) on the numbers of times participants pressed the space bar. No main effect of agent intention was observed ($\beta = 0.59$, 95% CI [−1.09, 2.28], $p = .491$). In general, participants pressed the space bar more often when playing against robots ($M = 27.87$, $SD = 21.86$) than against humans ($M = 26.30$, $SD = 23.03$) (Fig. 2A). Pairwise post-hoc tests on the interaction between agent type and intention were carried out with the emmeans package (v1.4.7) [25]. When playing against the competitive robot ($M = 29.09$, $SD = 22.25$), participants pressed the

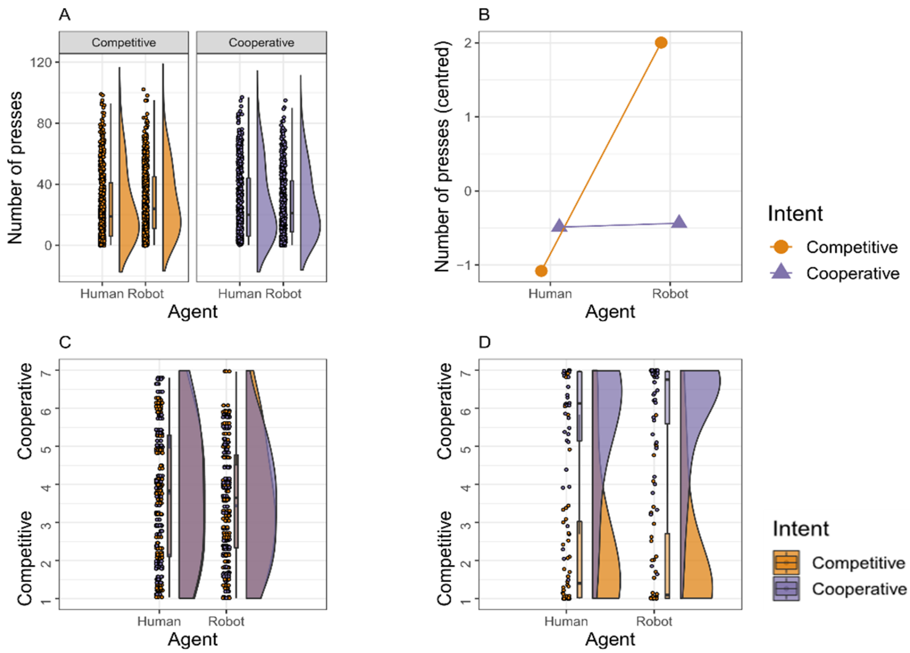

Fig. 2. (A) Number of presses in bar game per agent. (B) Interaction between agent and intent on centered number of presses. (C) Cooperativeness ratings per agent in main experiment. (D) Cooperativeness ratings per agent in validation experiment.

space bar more often than when playing against the cooperative robot (M = 26.65, SD = 21.40), t(2193.0) = 2.84, p = .024 (Fig. 2B). However, no clear difference emerged when comparing the competitive robot and the competitive human (M = 26.00, SD = 23.08), t(87.6) = -2.63, p = .049. Likewise, there was no significant difference found in the comparisons between competitive human and cooperative human (M = 26.60, SD = 22.99), t(2193.0) = -0.69, p = .902, competitive human and cooperative robot, t(87.6) = -0.55, p = .947, competitive robot and cooperative human, t(87.6) = 2.12, p = .154, or cooperative human and cooperative robot, t(87.6) = 30.04, p = 1.000.

3.2 Attitude Results

Preferential Ranking of Agents. In the result of our mixed effects ordinal regression model, agent type (odds ratio = 1.34, 95% CI [0.37, 4.90], p = .658), agent intention (odds ratio = 1.19, 95% CI [0.34, 4.09], p = .787), or ranking timing (odd ratio = 1.16, 95% CI [0.50, 2.67], p = .724) did not influence participants' preferential ranking towards the four agents.

Cooperativeness Slider Rating. Participants' cooperativeness ratings were significantly influenced by the interaction between agent type and agent intention (β = −0.28, 95% CI [−0.52, −0.04], p = .02), but not by the main effect of agent type (β = −0.06, 95% CI [−0.58, 0.41], p = .804) or agent intention (β = 0.19, 95% CI [-0.32, 0.71], p = .462). The cooperative human agent was rated most cooperative (M = 3.81, SD = 1.71), whereas the cooperative robot was rated most competitive (M = 3.47, SD = 1.42) among the four agents (competitive human: M = 3.62, SD = 1.63; competitive robot: M = 3.56, SD = 1.59). However, follow-up post hoc tests did not reveal any significant differences in the following pairs: competitive human vs. cooperative human (t(52.5) = −0.74, p = .883); competitive human vs. competitive robot (t(53.8) = 0.25, p = .995); competitive human vs. cooperative robot (t(47.0) = 0.44, p = .972); cooperative human vs. competitive robot (t(47.0) = 0.72, p = .888); cooperative human vs. cooperative robot (t(53.8) = 1.43, p = .486); competitive robot vs. cooperative robot (t(52.5) = 0.34, p = .986) (Fig. 2C). This is in contrast with the ratings in the validation study, where we observed a very clear distinction in cooperativeness slider ratings between the agents that were framed as cooperative and competitive in the videos (Fig. 2D).

Socialness Slider Rating. Participants' socialness ratings were significantly impacted by agent type (β = −0.55, 95% CI [−0.96, −0.15], p = .008) but not by agent intention (β = 0.12, 95% CI [−0.30, 0.54], p = .577) nor the interaction between agent type and intention (β = -0.20, 95% CI [-0.42, 0.02], p = .079). Participants rated humans (M = 3.79, SD = 1.50) as more social than robots (M = 3.14, SD = 1.33).

Cooperativeness Forced Choice. CNeither agent type (odds ratio = 0.46, 95% CI [0.11, 1.93], p = .288) nor agent intention (odds ratio = 0.74, 95% CI [0.50, 1.08], p = .118) was found to influence participants' forced choices of whether an agent was cooperative or competitive. This is surprising, given that in the validation study there was a clear strong effect of intent on the forced choices. Agents were consistently labelled as either cooperative (cooperative human: n = 32, cooperative robot: n = 33) or competitive (competitive human: n = 34, competitive robot: n = 34).

4 Discussion

We investigated the impact of human—robot encounters on people's attitudes and behaviors in the context of a simple online competitive game. Participants observed human—robot dyads interacting either cooperatively or competitively and were then led to believe they were playing a competitive game against algorithms informed by these agents' behaviors (while in reality, they were playing against the computer).

Third-party encounters influenced participants' competitiveness during game play, but had no influence on attitudes reported towards the observed agents. The main finding in our study was that participants showed higher game competitiveness (i.e., pressed the space bar more frequently) toward robotic agents than human agents, especially when the agents were framed as competitive in the observation phase. However, the findings on attitude change towards robots were inconsistent. Our results suggest that people's perceived cooperativeness of the agents was influenced by the interaction between agent type and agent intention, and that people perceived human agents as more social than robotic agents. Below we discuss these findings in detail.

Participants' increased competitiveness towards robotic compared to human opponents fits with previous research, in which participants behaved more competitively toward a robot than a human in economic games [26]. Our study further showed that such discriminatingly competitive behaviors toward robots could be diminished by observing cooperative human—robot encounters before engaging in an HRI. After participants observed the human and robotic agents cooperating in short videos, they responded similarly to cooperative robots and cooperative humans in the competitive online game. Notably, the effect of human–robot encounters we found on game behaviors existed regardless of the agents' actual behaviors when people directly interacted with them. Participants in the present study showed the highest game competitiveness towards the robot framed as competitive in the observation phase, even though all agents' game behaviors (behavioral competitiveness) remained consistent according to pre-programmed difficulty levels. These findings highlight the effects of third-party encounters on observers' behaviors, and relate to previous studies documenting the persistent impact of first impressions on people's behaviors during HRIs [27, 28].

Regarding the impact of human–robot encounters on participants' attitudes towards the agents, the present findings were inconsistent. First, encounters of cooperative and competitive human—robot dyads had no effect on participants' agent preference rankings, either in the pre-preference or post-preference tasks. This might suggest that the third-party encounters of cooperative and competitive HRI were irrelevant and thus did not influence people's preferences towards the agents in our experiment. A study by Huisman and colleagues [29] showed that the perceived politeness of virtual robots is not affected by cooperativeness or competitiveness of an agent during a game. However, other research reports that perceived warmth, competence, and personality of a robot are more crucial factors in our preferences towards robots [30, 31]. Future studies could consider manipulating these factors in human—robot encounters to investigate the subsequent impact on people's preferences towards the observed agents.

The impact of cooperative and competitive human—robot encounters on people's perceived cooperativeness towards the agents was not robust in our study. Our post hoc analyses did not reveal any difference between any agent pairs, albeit the significant interaction between agent type (human/robot) and agent intention (cooperative/competitive) emerged for participants' cooperativeness slider rating towards the agents. Similarly, participants' forced choices regarding the cooperative and competitive nature of an agent were not influenced by agent intention framing or agent type. These results suggest that the agent intention manipulation was perhaps not strong enough to shape participants' perceived cooperativeness of the agents, which contradicted the results of our validation studies where competitive and cooperative framing was accurately differentiated by participants' cooperativeness rating. Another possible explanation for the ineffective agent intention manipulation was the competitive nature of the game. In the bar game used here, participants and agents had opposite goals to achieve and therefore all the agents might be perceived as competitive by the participants. This competitive game experience may obscure the manipulation of agent intention in the prior observation phase. Previous studies have pointed out that the perceived competitiveness in environments or agents can shape people's attitudes. For examples, Mutlu and colleagues found that people had more positive attitudes towards the ASIMO robot in a cooperative game context than in a competitive game context [32]. Even when researchers did not intend to frame the robot as competitive, participants can be sensitive to robot's non-cooperative decisions and responded to these reciprocally [33]. Therefore, future research on this topic may choose to make more judicious decisions when designing a HRI context and manipulating an agent's intention, to ensure an agent's attribute in third-party encounters is not in contrast with how the agents behave in the actual HRI.

Finally, our study revealed a significant effect of agent type (human/robot) on participants' socialness ratings towards the agents. Human agents were rated as more social than robotic agents. This is not surprising since we have extensive social experience with human interaction partners, whereas robots are only emerging in social contexts. However, as robots become more prevalent, especially in social contexts, it could be possible to amplify a robots' perceived socialness by changing [34]. It would be valuable for future research to explore whether third-party encounters of robots with different characteristics lead to varying degrees of perceived socialness, as well as to further identify which factors are key to shaping the attribution of socialness to robots.

In summary, the current study provides important evidence documenting the influence of observed human—robot encounters on people's behaviors towards the observed robots. Specifically, in our online game environment, participants behaved more competitively when competing against the robot previously framed as competitive than the robot framed as cooperative. However, this work will require follow-up research to determine the generalizability of people's behaviors during online games to behaviors displayed during real-world HRI that takes place with embodied (as opposed to virtual) agents. Although online studies can provide insightful evidence [35–36], physical embodiment is an important factor that shapes our perceptions of and behaviors towards robots [34, 38–40]. For example, people report more enjoyment and engagement during embodied HRI than during virtual HRI [38]. Future research could further extend the current exploration of human—robot encounters to other contexts, or to other aspects of social behaviors, as well as further substantiate the link between people's attitudes and behaviors during HRI. By doing so, researchers should be able to provide further and clearer evidence of the potential utility of third-party encounters to promote the social quality of real-life HRIs, which should hopefully lead to more effectively and usefully embedded social robots in human society.

5 Competing Interests

The authors declare that they have no competing interests.

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