Trust is not all about performance:
trust biases in interaction with humans, robots and computers

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Abstract

Trust is essential for sustaining cooperation among humans. The same principle applies during interaction with computers and robots: if we do not trust them, we will not accept help from them. Extensive evidence has shown that our trust in other agents depends on their performance. However, in uncertain environments, humans may not be able to estimate correctly other agents’ performance, potentially leading to distrust or over-trust in peers and machines. In the current study, we investigate whether humans’ trust towards peers, computers and robots is biased by prior beliefs in uncertain interactive settings. Participants made perceptual judgments and observed the simulated estimates of either a human participant, a computer or a social robot. Participants could modify their judgments based on this feedback. Results show that participants’ belief about the nature of their partner biased their compliance with the partners’ judgments, although the partners’ judgments were identical. Surprisingly, the social robot was trusted more than computer and human partner. Trust in the alleged human partner was not fully predicted by its perceived performance, suggesting the emergence of normative processes in peer interaction. Our findings offer novel insights in the understanding of the mechanisms underlying trust towards peers and autonomous agents.
**Introduction**

Trust is one of the hallmarks of sustainable cooperation between humans. Trusting others is fundamental to cooperate with our peers and accept help and advices from them. Likewise, trust is fundamental in the use of automation: indeed, the more we trust it, the more we use it (Desai et al., 2009). In the next future, autonomous robots will play a more and more central role in our society and they will assist us in a wide range of contexts, including education, care-giving and industry. Crucially, extensive research in human-robot interaction has highlighted that trust is essential for humans to use information provided by robots and cooperate with them, especially in uncertain or risky situations (Hancock et al., 2011).

Trust has been conceptualized differently in human-human and human-robot interaction literatures (Flook et al., 2019). Research on human-human interaction historically put the accent on a “relational” dimension of trust. In this sense, trust denotes the acceptance of a condition of vulnerability or a delegation of responsibility towards peers (Flook et al., 2019; Lee & See, 2004; Mayer et al., 1995; Ullman & Mall, 2018). Along human evolution, social norms have been established to promote mutual trust and cooperation between individuals and protect them from the emergence of defective behavior. For instance, humans tend to normatively conform to the opinion of their peers in order to affiliate with them and control reputation in the group (Asch, 1951; Cialdini & Goldstein, 2004, Claidière & Whiten, 2012; Mahmoodi et al., 2018; Zonca et al., 2021) and reciprocate trust in repeated interactions (e.g., De Quervain et al., 2004; King-Casas et al., 2005; Krueger et al., 2007; McCabe et al., 2001; Singer et al., 2006).

However, this “relational” dimension of trust is often in conflict with its “capacity” dimension, which is grounded in the perceived reliability and competence of peers. Indeed, humans assign weights to others’ opinions incorporating direct and indirect signals of others’ competence, including reliability (De Martino et al., 2017; Park et al., 2017), confidence (Bahrami, 2010; Sniezek & Van Swol, 2001) and expertise (Bonaccio & Dalal, 2010; Boorman et al., 2013; Sniezek et al., 2004). On the contrary, research on trust in human-robot interaction historically focused on competence and reliability of robots (Ullman & Mall, 2018). Extensive evidence has shown that the main determinant of trust in automation is its performance (Billings et al 2012; Hancock et al., 2011; van den Brule et al., 2014; Wright et al., 2019). In fact, when competence and reliability of robotic partners is known, individuals rapidly lose trust in the system in presence of inefficient behavior or failures (Desai et al., 2012; Rossi et al., 2017; Salomon et al., 2018), potentially leading to disuse of the robotic system (Lussier et al., 2007; Sanders et al., 2011).

Nonetheless, in some circumstances it might be difficult to determine the reliability of an interacting partner (human or robot), due to the absence of exogenous feedback about own and others’ performance. In these contexts, our prior beliefs about the relational and informational characteristics of our partner (s) may distort our process of weighting of information by reliability. On the one hand, extensive evidence in human-human interaction has shown that uncertainty leads to egocentric advice discounting (EAD; Yaniv, 2004; Yaniv & Kleinberger, 2000): people tend to over-estimate their own abilities in respect to others (Heyes, 2012; Soll & Larrick, 2009), over-discount socially acquired information (Gardner & Berry, 1995; Toelch et al., 2014) and under-estimate own responsibility for
undesired outcomes in cooperative settings (Sedikides et al., 1998; Duval & Silvia, 2002). On the other hand, research in human-robot interaction revealed that trust towards robots intrinsically tied with the uncertainty of the task solution: individuals typically trust robots only if they are unsure about the action to take (Hertz & Wiese, 2016). Humans tend to trust robots in functional tasks (i.e., tasks in which the robot has to fulfill a concrete goal through actions or quantitative judgment) rather than social ones (i.e., judgments or decisions on social issues), as shown in recent studies (Gaudiello et al., 2016; Ullman et al., 2021). Moreover, recent studies have shown that, in uncertain and risky settings, people sometimes trust automation more than they should (Kaniarasu et al., 2013). For instance, several studies have shown that people tend to over-comply with the instructions of robots, even if they have previously show faulty or unreliable behavior (Aroyo et al., 2018, 2021; Robinette et al., 2016; Salem et al., 2015). Altogether, previous research on trust in human-human and human-robot interaction reveals the existence of a series of relational, cognitive and normative mechanisms that influence the process of trust building between humans and peers or robotics agents.

In the current study, we aim at investigating how our beliefs about the nature of a partner (human peer, humanoid robot, or computerized agent) may modulate our trust towards them in the context of quantitative, perceptual judgments. We designed a novel experimental paradigm consisting of two tasks (Perceptual inference task and Individual trust task). Participants were split in three between-subject experimental conditions (Computer, Robot, and Human). In all the conditions, participants performed the Perceptual inference task by estimating the length of visual stimuli without any feedback on a touch-screen tablet. In the Individual trust task, participants in the three conditions believed to interact with three different partners: a computerized agent, a humanoid robot iCub (Metta et al., 2008, 2010) or another human participant. Participants performed the same perceptual estimates as in the previous task, but this time they received (on the same tablet) trial-by-trial feedback revealing the judgment made by their partner. Then, in each trial, after observing the partner’s response, participants could modify their own estimate by selecting any position between their own and their partner’s estimate (final decision). The participants’ shift from their own original estimate towards the one of the partner in their final decision has been used as an index of trust in the partner’s response. To guarantee that the manipulation modulated only prior beliefs about the interacting partner, we did not provide any feedback about the participant’s or the partner’s accuracy. Moreover, the partner’s responses in all the conditions were generated by the same probabilistic algorithms. Using this design, we had the possibility to analyze trust mechanisms built upon precise, quantifiable and well-known mechanisms underlying individual behavior. The behavior of participants and their relative partner were therefore operationalized and quantified with millimeter precision, and could be precisely and transparently tracked by the interacting partners along the task though on-line feedback. At the same time, our experimental manipulation allowed us to explore whether and how our prior beliefs about the nature of the interacting partner could modulate participants’ trust. By comparing participants’ expression of trust across conditions and by investigating the
endogenous and exogenous mechanisms modulating trust towards different partners, we hope to offer new insights about the processes sustaining trust in human-human and human-robot interaction.

**Materials and methods**

**Overview: participants and procedure**

Seventy-five (75) participants participated in our study (42 females, mean age: 32.96, SD: 12.30). All participants completed the entire experimental paradigm, which included two different tasks that were performed in this exact order: *Perceptual inference task* and *Individual trust task*. Participants were split in three experimental groups of 25 participants each, leading to three between-subject experimental conditions: *Computer*, *Robot* and *Human*. In all the conditions, participants performed the *Perceptual inference task* alone and then they performed the *Individual trust task* with a partner. The difference between the three conditions lied in the participants’ belief about the nature of the interacting partner: a computer (*Computer* condition), a humanoid robot iCub (*Robot* condition) or a human participant (*Human* condition). One of the main goals of the current study was to study how prior beliefs on the nature of an interacting agent could bias participants’ trust towards them. Therefore, we aimed at designing experimental conditions that could be perfectly comparable between each other. In fact, the partner’s behavior in all conditions was controlled by the same computer algorithms. All the participants performed the task using a touch screen tablet through which the participant and the (alleged) partner (computer, robot or human) could 1) make choices and 2) receive on-line feedback on the choices of the partner.

Participants in the *Robot* condition could not see their robotic partner while performing the tasks. We chose not to design a task consisting in an on-site physical interaction between participants and the robotic agent to prevent participants from inferring the robot's ability in the task by observing the characteristics and kinematics of its movements. In fact, we wanted participants to acquire knowledge about the robot's ability just by observing its responses, in order to have full control of the robot’s feedbacks and ensure the comparability with *Computer* and *Human* condition. Nonetheless, participants in the *Robot* condition, before starting the experimental tasks, had the possibility to meet their supposed partner in the experiment (a humanoid robot iCub). In this way, they could get an idea of the type of agent they would have interacted with. In this encounter, we aimed to convey the impression that the robot could 1) act as a social and intentional agent, which knew that it would have played a joint task with the human participant and 2) physically perform the same task that the participant would face in their experimental session. For a complete description of the participants’ encounter with the robot, see the next paragraph “Introducing the humanoid robot iCub”. Afterwards, participants in the *Robot* condition were conducted in a new room to perform the experimental paradigm.

Participants in the *Human* and *Computer* conditions underwent the same experimental paradigm as the ones assigned to the *Robot* condition, but they did not meet the robot before the start of the experimental protocol. In the
Human condition, participants were told that their partner had been recruited with the same modalities and has been performing the task in a neighboring experimental room (see “Cover stories and debriefing” paragraph). Participants in the Computer condition were informed that the partner’s responses were computer-generated.

For all participants, the experimental paradigm was carried out in a dimly lit room, to ensure an optimal visibility of the stimuli on the screen. Participants seated in front of a wide touch screen (43.69 x 24.07 cm), at a distance that allowed participants to see the visual stimuli and reach the screen with their finger. In order to allow participants to respond with high spatial accuracy, we provided a touch-pen with an ultrathin tip. Before beginning the experimental tasks, written instructions were given and participants were allowed to ask questions. Participants were told that their reimbursement would have been calculated based on their performance and, in particular, on the accuracy of both their initial and final estimates in both tasks. The accuracy of the partner(s) was not supposed to have an impact on participants’ outcomes, and viceversa. However, everyone received a fixed amount (15 euros) at the end of the experiment, following the guidelines of the Italian Institute of Technology concerning the application of a fair reimbursement for voluntary participation in experimental research. The final debriefing revealed that all participants, during the experiment, believed that their final reimbursement would be affected by their performance. Eventually, we extensively debriefed participants about the experimental procedures, the reasons underlying the modality of reimbursement and the goals of our research, in accordance with the relevant ethical guidelines. The study was approved by the local ethics committee (Azienda Sanitaria Locale Genovese N.3, protocol: IIT_wHiSPER) and all participants gave informed consent.

Introducing the humanoid robot iCub

In order to assess participants’ trust in a context of human-robot interaction (Robot condition), we used the humanoid robot iCub, which is an open source humanoid robot for research in embodied cognition and artificial intelligence (Metta et al., 2008, 2010).

The robot has 53 actuated degrees of freedom that allow fine-grained movements of head, arms, hands, waist and legs. It is endowed with sensors and actuators allowing it to generate controlled and precise actions and direct its attention towards objects and individuals. The robot possesses lines of red LEDs representing mouth and eyebrows mounted behind the face panel to produce facial expressions and simulate speech. All these characteristics ensure that iCub can show human-like appearance and behavior (Metta et al. 2008; Tsagarakis et al., 2007) and can be perceived as an intentional agent (Sciutti et al., 2013a; Wiese et al., 2017) that generates autonomous actions to accomplish specific goals. For the purposes of the current experiment, we aimed at conveying the impression that the robot could 1) act as a social and intentional agent, which was aware of the presence of the participant and knew about the upcoming joint experiment and 2) physically perform the same task that participants would have faced in their experimental session.
To accomplish these goals, participants in the Robot group had a meeting with iCub before starting the experimental tasks. Before the participants’ arrival, iCub was placed in front of a touch-screen tablet, which was identical to the one that participants would use during their experimental session. Once the participant had arrived at the research center, one experimenter accompanied them in a dedicated room with iCub, while another experimenter controlled the robot from the sidelines. The robot performed a series of predetermined actions (identical for all participants) by a custom-made script. The researcher controlling the robot managed the timing of the robot actions to simulate a natural interaction with the participant. Once the participant had entered in the room, iCub turned towards them saying hello with its voice and waving its hand. The participant was accompanied in front of the robot, so that iCub could track their face and direct its attention towards them. Then the robot introduced itself and told the participant that they would play a game together; meanwhile, iCub continued to look at the participant and follow their head movements. These actions aimed at signaling that iCub was aware of the presence of the participant and knew that would interact with them in the upcoming experiment. Eventually, iCub said goodbye to the participants, turned towards the tablet and announced that it was ready to play. To give the impression that iCub could observe stimuli on the touch-screen tablet and reach it with its hand to perform the task, it also leaned forward and moved its right arm and hand towards the tablet, pointing in the direction of the screen with its right index, as if it was ready to touch it. At this point, the participant was guided in another room to start the experimental session. We highlight that participants did not receive any direct or indirect information about the robot’s accuracy in the task, to allow clean comparison between the three experimental conditions.

**Tasks description**

**Perceptual inference task**

The perceptual inference task was identical for all participants in the three experimental conditions. In each trial (Fig. 1a), participants saw two consecutive light flashes (red disks of 0.57 cm of diameter, duration 200 ms) appearing on a visible horizontal white line crossing the whole screen at its central height. The first disk appeared at a variable distance from the left border of the screen (0.6–6.6 cm). After its disappearance and an inter-stimulus interval of 200 ms, a second disk appeared at a variable distance to the right of the first disk. The target stimulus length (s) has been defined as the distance between the first and the second disk. The target stimulus length was randomly selected from 11 different sample lengths (min: 8 cm, max: 16 cm, step: 0.8 cm). Participants were then asked to touch a point on the horizontal line, to the right of the second disk, in order to reproduce a segment (connecting the second and the third disk) that matched the target stimulus length. Right after the participant’s screen touch, a third red disk appeared in the selected position. We did not provide any feedback about the accuracy of the response. The task consisted of 66 trials. At the end of the task, participants were asked to evaluate from 1 to 10 the accuracy of their perceptual estimates.
Fig 1. a) Perceptual inference task. Participants were presented with a red disk that appeared on a horizontal line and then disappeared after 200 ms, followed by another disk appearing and disappearing after 200 ms to the right of the first disk. Participants had to touch a point, to the right of the second disk, in order to reproduce the stimulus length (s’), defined as the distance between the first and the second disk (s).

b) Expected perceptual phenomena. Due to perceptual mechanisms such as central tendency and scalar variability, we expect a distortion in the participants’ pattern of perceptual inferences. Due to central tendency, participants should underestimate long stimuli and overestimate short stimuli; because of scalar variability, the central tendency effect should be stronger for long distances, leading to a general under-estimation of the mean of the reproduced length distribution (M(S’)).

Individual trust task
At the beginning of each trial, participants had to make a perceptual inference as in the Perceptual inference task. Right after their estimate, a vertical red line with the word YOU appeared at the exact response location. Participants were told that, during this interval, the same stimulus would be presented also to their interacting partner (computer in the Computer condition, iCub in the Robot condition, human participant in the Human condition), that would make its own perceptual estimate concerning the same stimulus. After the participants' estimate, the other agent's estimate was shown, marked with the word PC (Computer condition), ICUB (Robot condition) or BP (Blue Player, Human condition) in blue (Fig. 2a). Moreover, participants were told that also their response would have been shown to their interacting partner.

Right after the counterpart's estimate, participants had the opportunity to make a final decision: they could decide any position between their previous response and the partner's response, but not outside this range. In these terms, participants’ final decisions express the relative weight assigned to the judgment of the two interacting partners. After the participant’s final decision, a green dot and a vertical green line with the word FINAL marked the position chosen by the participant. Participants were told that their partner could observe the position of both their perceptual estimates and their final decisions. The task consisted of 66 trials divided in three blocks by two pauses.
of all the three responses (participant's estimate, partner's estimate and final decision) remained visible on the screen for 1 s.

At the end of the task, participants were asked to evaluate from 1 to 10 their own and the other agent's accuracy in the perceptual estimates, without taking into account their final decisions.

**Fig 2.** First participants had to reproduce the lengths of visual stimuli, as in the Perceptual inference task. Participants were told that the very same stimuli would have been presented also to their partner (other agent: OA), which was supposed to be a computer in the Computer condition, a humanoid robot in the Robot condition and a human participant in the Human condition. Participants were told that the partner would have chosen a point to reproduce the length of the presented stimulus. After the participants’ estimate, the partner’s simulated estimate was shown and then one of the two agents had the opportunity to make a final decision by choosing any position between own and partner’s estimates. The index of trust was defined as the adjustment towards the partner in the final decision ($a$) divided by the distance between the two agents’ responses ($d$).

**Agents’ behavior**

**Agents’ perceptual estimates**

The simulated perceptual estimates of the interacting agent (computer, robot or human participant) were based on the same probabilistic algorithm. In each trial, the position of its perceptual estimate was randomly chosen from a gaussian distribution centered at the correct response (SD: 1.52 cm). The standard deviation of the response error distribution was chosen to maintain a balance between accuracy, variability and credibility. We aimed at controlling the variance of the algorithm in order to prevent participants from recurrently observing extremely high discrepancies between the two responses, which would have affected considerably the perceived reliability of the partners. For this reason, the standard deviation of the response distribution of the algorithm was set to be 25% lower than the observed standard deviation of participants’ responses, as estimated in a pilot study. However, we also considered the possibility that few participants could be very accurate in their perceptual inferences. In this case, the participant and their partner would have selected close responses very often, preventing the emergence of variability in participants’ final decisions. Therefore, in half of the cases in which the sampled estimate of the
algorithm was rather close to the one of the participant (i.e., d < 0.5 cm), the algorithm re-sampled a new response from the distribution (i.e., until d > 0.5 cm).

This response distribution was used for all the perceptual estimates in both the Perceptual inference task and the Individual trust task.

Data analysis and hypotheses

Perceptual inference task

Due to of the well-known phenomenon of central tendency in quantity judgments (Hollingworth, 1910, Jazayeri and Shadlen 2010), we predict that participants’ estimates in the Perceptual inference task will gravitate towards the mean magnitude the presented visual stimuli (Figure 1b). Therefore, short distances should be over-estimated and long distances should be under-estimated in the process of length estimation. The mechanism of central tendency allows humans to cope with sensory uncertainty in the presence of noise in the incoming sensory information, allowing to increase the reliability of perception (Sciutti et al., 2014). We quantified the effect of central tendency by computing the regression index, defined as the difference in slope between the identity line (i.e., veridical reproduction of stimuli) and the best linear fit of the reproduced lengths. A regression index of 1 indicates complete regression to the mean. The algorithm underlying the responses of the participants’ partner, in all the experimental conditions, shows a regression index close to 0, since the normal distribution from which the current estimate is drawn is centered on the correct response.

Central tendency should be more pronounced with higher levels of uncertainty associated with the current perceptual estimation. In this regard, since this phenomenon follows Bayesian principles and since the standard deviation of the reproduced stimulus linearly increases with its magnitude (scalar variability effect, Petzschner et al., 2015), we expect participants to markedly under-estimate long distances, whereas short distances should be over-estimated to a lower extent (Figure 1b). Therefore, we predict that the mean of the distribution of the reproduced lengths will be lower than the one of the presented lengths. To investigate this effect, we computed the average reproduced length to analyze the spatial characteristics of the distribution of the reproduced responses. The average reproduced length should be lower than the one produced by the interacting agent, whose response distribution is centered on the correct response and not influenced by scalar variability.

For the purpose of subsequent between-condition analyses in the Individual trust task, we compared the performance of the three groups (Computer, Robot and Human) to ensure that they had similar in the Perceptual inference task. The main parameter of accuracy that has been used throughout the paper was the estimation error, computed as the absolute difference (in cm) between the estimated length and the actual stimulus length divided by the actual stimulus length, in order to give equal weights to trials including short and long visual stimuli. This parameter directly depends on perceptual phenomena such as central tendency and scalar variability.
**Individual trust task**

In the *Individual trust task*, participants’ made their perceptual estimates as in the previous task and then could observe the partner’s estimate concerning the same stimulus. Then they were asked to make a final decision, placing their final response in any position between their own and the partner’s response. First, we analyzed participants’ performance in terms of *estimation error*, in comparison with the *Perceptual inference task*, to investigate whether the additional feedback about the partner estimates (which were particularly accurate) was used by participants for learning purposes. Concerning participants’ final decisions, an index of *trust* was computed as the distance between the participants’ final and initial response divided by the distance between the two agents’ initial estimates. Therefore, the index of *trust* can take any value between 0 and 1, where 0 indicates a final decision coinciding with the participant’s own estimate and 1 corresponds to a final decision coinciding with the partner’s estimate. *Trust* was compared across experimental conditions (*Computer, Robot and Human*) to investigate the effect of prior beliefs on the processing of the other agent’s feedbacks. Moreover, this index was analyzed as a function of distance from the partner’s response, which was the only explicit feedback that participants could use to assess the relative accuracy of the two agents. We also explored the relationship between participant’s trust in the partner and *estimation error* to reveal if participants’ accuracy, which was unknown to the participants’ themselves, could explain their willingness to follow the partner’s opinion. Furthermore, we analyzed participant’s performance ratings concerning own and partner’s accuracy (from 1 to 10), which were collected at the end of the *Individual trust task*.

**Statistical data analysis**

Most of the analyses reported in this work focus on analysing variation of task-related dependent variables (i.e., trust, estimation error) as a function exogenous experimental factors (i.e., experimental conditions) and endogenous predictors (i.e., distance from other agent’s response, performance ratings). Moreover, throughout the paper we also directly compared individual variables (e.g., trust, estimation error, performance ratings) across experimental conditions and groups. Since these individual variables occasionally show some degree of skewness and, in some conditions, show a violation of the normality distribution assumption, we used non-parametric tests (Wilcoxon signed-rank test, Wilcoxon rank-sum test, Kruskal-Wallis test) through the entire paper for consistency. All tests are two-tailed and report z statistic, p. value and effect sizes (r, $\eta^2$). The formulas used for the calculation of the effect sizes can be found in Cohen (2008) and Fritz et al. (2012): $r = Z/\sqrt{N}$ (total number of observations); $\eta^2 = Z^2/N$. For the same reason, we used non-parametric correlation tests (Spearman’s rank correlation). Multiple comparisons have been treated using Bonferroni correction.

In regression analyses, we report unstandardized (B) and standardized ($\beta$) regression coefficients, t statistics and p.value. In the Supplementary information, we report complete regression results including tables with standard
errors and confidence intervals. In one occasion, we used a mixed-effect model of trial-by-trial trust with random effect at the subject level. The random effect has been applied to the intercept to adjust for the baseline level of influence of each subject and model intra-subject correlation of repeated measurements. Specification and results of all regression models have been described in detail in the Supplementary information.

All analyses include the entire sample of 75 subjects and all trials of the three experimental tasks.

Cover stories and debriefing
Before starting the experiment, participants were told that they would perform the task with a partner, which varied depending on the experimental condition (a computer algorithm in the Computer condition, a humanoid robot iCub in the Robot condition, a human participant in the Human condition). All participants performed the task alone in a dedicated experimental room on a touch-screen tablet. Participants in the Computer condition were simply told that the partner’s responses were computer-generated. Participants in the Robot condition had a short meeting with the robot before starting the experiment (see “Introducing the humanoid robot iCub” paragraph) and then performed the task in a different experimental room. They were told that, in the meantime, the robot would actively perform the task on an identical tablet. Participants in the Human condition were told that their partner has been recruited with the same modalities and has been performing the experiment in a neighboring experimental room. At the end of the experiment, we debriefed all participants asking them indirect questions about the experiment and their partner to assess whether they have believed the cover story. All participants indeed believed the cover story.

Eventually, we extensively debriefed participants about the experimental procedures, the reasons underlying the modality of the experiment and the goals of our research, in accordance with the relevant ethical guidelines.

Results
Perceptual inference task
First, we analyzed the patterns of perceptual estimates of participants in the three experimental conditions (Computer, Robot and Human, Figure 3). Analysis of the regression index reveals that participants in all conditions show a significant effect of central tendency (Computer: 0.46 ± 0.24; Robot: 0.38 ± 0.23; Human: 0.51 ± 0.26. Wilcoxon signed rank-test, null hypothesis: regression index = 0. Computer: z = 4.29, r = 0.86, η² = 0.74, p < 0.001; Robot: z = 4.29, r = 0.86, η² = 0.74, p < 0.001; Human: z = 4.34, r = 0.87, η² = 0.75, p < 0.001. These results are significant at the Bonferroni-corrected threshold for 3 comparisons). Furthermore, results show a strong scalar variability effect: the participants’ average reproduced length was significantly lower than the mean of the presented stimulus distribution in all the three conditions (Computer: 10.48 ± 1.39; Robot: 11.08 ± 1.25; Human: 10.51 ± 1.49. Wilcoxon signed rank-test, null hypothesis: average reproduced length = 12. Computer: z = - 3.86,
r = 0.77, η² = 0.60, p < 0.001; Robot: z = -3.03, r = 0.61, η² = 0.37, p = 0.002; Human: z = -3.51, r = 0.70, η² = 0.49, p = 0.004. Results are significant at the Bonferroni-corrected threshold for 3 comparisons).

Then we investigated the comparability of our three experimental groups by testing for the presence of a between-group difference in terms of estimation error. Results show that the three groups did not differ in terms of estimation accuracy (Computer: 0.20 ± 0.05; Robot: 0.19 ± 0.06; Human: 0.21 ± 0.05. Kruskal-Wallis test, χ² = 3.10, p = 0.212).

**Fig. 3. a) Responses in the Perceptual inference task in Computer, Robot and Human conditions.** Gold (Computer), light green (Robot) and scarlet (Human) dots represent participants’ reproduced lengths for each presented length. Orange (Computer), dark green (Robot) and red (Human) dots represent the participants’ mean reproduce length for each presented stimulus. Orange, dark green and red lines represent the linear fit between presented and reproduced lengths in Computer, Robot and Human conditions, respectively. Black lines represent the identity line (veridical reproduction). The pattern of responses in all groups reflect the emergence of central tendency and scalar variability effects depicted in Fig. 1b. Indeed, the slope of the reproduced lengths is flatter than the identity line, indicating a regression towards the mean in the reproduce lengths (i.e., central tendency effect). Moreover, we observe that this effect is more pronounced for relatively longer stimuli, resulting in a general under-estimation of the presented visual stimuli. b) **Average estimation error in Computer, Robot and Human groups.** The three experimental groups are comparable in terms of estimation error, which is computed as distance (in cm) from the correct response / stimulus length (Kruskal-Wallis test, χ² = 3.10, p = 0.212).

**Individual trust task**

First, we underline that participants’ estimation accuracy was markedly lower than the one of their partner in all the three experimental conditions (Wilcoxon rank-sum test on estimation error. Computer: z = 6.06, r = 0.86, η² = 0.73, p < 0.001; Robot group: z = 6.06, r = 0.86, η² = 0.73, p < 0.001. Human group: z = 5.64, r = 0.80, η² = 0.64, p <
Results significant at the Bonferroni-corrected threshold for 3 comparisons). We did not find any difference in terms of estimation error across experimental conditions (Kruskal-Wallis test, $\chi^2(2) = 0.55$, p = 0.759). Moreover, in all conditions, participants’ estimation error was comparable to the one we observed in the Perceptual inference task (Wilcoxon signed-rank test on estimation error. Computer: $z = 0.040$, r = 0.01, $\eta^2 = 0.00$, p = 0.968; Robot: $z = -0.740$, r = 0.10, $\eta^2 = 0.01$, p = 0.459; Human: $z = 0.417$, r = 0.06, $\eta^2 = 0.00$, p = 0.677), suggesting that the partner’s response was not used as a feedback for perceptual learning.

This inability to use the partner as an information source for learning was associated with a strong distortion in the participants’ perception of own and partner’s performance. Specifically, participants did not recognize that their partner was more accurate than they were, since their performance ratings were even higher for their own accuracy (Computer: 6.28 ± 1.10; Robot: 6.4 ± 1.08; Human: 6.16 ± 1.43) than that of the partner (Computer: 5.52 ± 1.64; Robot: 6.24 ± 1.90; Human: 5.52 ± 1.48). A mixed-effects model with performance rating as dependent variable, agent (self or other), identity of the other agent (computer, robot or human) as independent factors and subject as random effect confirms the presence of an effect of agent (higher ratings for self than other, omnibus test: $\chi^2(1) = 6.14$, p = 0.013) but no effect of partner’s identity ($\chi^2(2) = 2.76$, p = 0.251) and interaction ($\chi^2(2) = 1.53$, p = 0.466).

In line with the egocentric bias observed in participants’ performance ratings, analysis of final decisions reveal that participants relied more on their own estimate than that of the partner (Average trust, Computer: 0.26 ± 0.13; Robot: 0.35 ± 0.16; Human: 0.23 ± 0.14. Wilcoxon signed rank-test, null hypothesis: average trust = 0.5. Computer: $z = 4.29$, r = 0.86, $\eta^2 = 0.74$, p < 0.001; Robot: $z = 3.51$, r = 0.70, $\eta^2 = 0.49$, p < 0.001; Human: $z = 4.37$, r = 0.87, $\eta^2 = 0.76$, p < 0.001. Results significant at the Bonferroni-corrected threshold for 3 comparisons).

Although participants in all groups showed an egocentric bias in their final decisions, their level of trust was statistically different across conditions (Kruskal-Wallis test, $\chi^2(2) = 7.67$, p = 0.022). We further explored this difference by running a regression with mean trust as dependent variable and experimental condition as dummy factor (Figure 4. Supplementary Information, model 1). Results reveal that the robot partner was trusted more than the human partner (Human – Robot, B = -0.12, p = 0.005) and the computer one (Computer – Robot, B = -0.08, p = 0.041). We did not found any difference between the Human and the Computer conditions (Human – Computer, B = -0.03, p = 0.410). These results do not change when controlling for participants’ mean estimation error (Supplementary Information, model 2). These differences are particularly interesting if we consider that the responses of the partner were identical across experimental groups. This reveals that the prior belief about the nature of the partner (computer, robot or human) played a crucial role in the processing and weighing of the partner’s estimates.
Fig. 4. a) **Average trust in the partner in the Individual trust task.** Bar plots of mean trust in *Computer, Robot* and *Human* conditions. Trust is computed as the participant’s shift (in cm) towards the partner’s response in the final decision divided by the distance (in cm) from the partner’s estimate. Therefore, this index reflects a relative index of trust ranging from full trust in the partner’s response (trust = 1) to full trust in participants’ own response (trust = 0). Participants in all groups trusted more their own estimate than the one of the partner (mean trust < 0.5). Trust was significantly different across conditions (Kruskal-Wallis test, $\chi^2(2) = 27.67$, $p = 0.022$). In particular, mean trust was higher in the *Robot* condition than in the other two conditions. Error bars represent between-subject standard error of the mean. ** * p < 0.001, * p < 0.05, linear regression with condition as dummy factor.

b) **Trust as a function of agents’ response distance.** Standardized (within-subject) trust plotted as a function of distance from the partner’s estimate. To obtain this graph, for each participant, we standardized trial-by-trial normalized distance between the estimates of the two agents (distance (cm) / stimulus length (cm)) to express each distance value in terms of deviation from the individual subject mean. We clustered standardized distances in six bins: 1) distance < -1 SD; 2) -1 SD ≥ distance < -0.5 SD; 3) -0.5 SD ≥ distance < 0 SD; 4) 0 SD ≥ distance < 0.5 SD; 5) 0.5 SD ≥ distance < 1 SD; 6) distance ≥ 1 SD. We also standardized, for each participant, trial-by-trial influence to express influence values in terms of deviation from individual influence means. Eventually, for each distance range, we averaged individual influence means across subjects. We report standardized regression coefficients and p. values obtained through a mixed-effect model analyzing the relationship between within-subject modulation of trust by agents’ response distance. We also report interactions effects assessing between-condition differences in the relationship between trust and response distance: *** p < 0.001.

Then we investigated if within-subject modulation of influence was linked to the perceived reliability of the current partner’s feedback. Therefore, we tested the relationship between influence and distance from the partner’s
response. We ran a mixed-effect linear regression with final decision as dependent variable, condition (Computer, Robot, Human), distance and their interactions as independent variables, with subject as random effect (Supplementary information, model 3). Results show a negative effect of distance on influence in all the three experimental conditions (Computer: \( \beta = -0.31, B = -0.44, z = -12.86, p < 0.001 \); Robot: \( \beta = -0.20, B = -0.30, z = -9.76, p < 0.001 \); Human: \( \beta = -0.04, B = -0.06, z = -1.98, p = 0.048 \)) groups: more specifically, participants’ influence decreased with the increase of the distance from the partner’s estimate (Fig. 4b). One the one hand, this effect suggest that participants’ trust was indeed modulated by the perceived reliability of the current partner’s feedback; one the other hand, it reveals that the existence of a discrepancy between the two interacting partners’ responses was interpreted by participants as a signal of the unreliability of the partner rather than themselves, confirming their egocentric bias. Nevertheless, we highlight the existence of interaction effects: the effect of distance was stronger in the Computer condition than in the other two conditions (Robot - Computer, \( B = 0.14, z = 2.99, p = 0.003 \); Human - Computer, \( B = 0.38, z = 8.40, p < 0.001 \)). Moreover, the effect of distance was stronger in the Robot than in the Human condition (Human - Robot, \( B = 0.24, z = 5.66, p < 0.001 \)). Altogether, interaction effects suggest that the nature of the partner determines the extent to which participants’ use the perceived reliability of the partner to modulate their expression of susceptibility to them. In particular, these results suggest that the more the partner show human-like or social characteristics, the less participants’ susceptibility depends on strictly informational characteristics based on the partner’s reliability. In this regard, we show that, in Computer and Robot conditions, participants’ average influence was strongly correlated with performance ratings (i.e., self–other rating. Computer: \( \rho = -0.66, p < 0.001 \); Robot: \( -0.58, p = 0.002 \). Results significant at the Bonferroni-corrected threshold for 3 comparisons) revealing that their final decisions strongly depended on the perceived competence of the partner. Nevertheless, this correlation was totally absent in the Human condition (\( \rho = 0.03, p = 0.897 \)). These findings underline a marked difference between participants’ willingness to rely on the judgment of either a mechanical agent or a peer. One the one hand, reliance on the judgments of a mechanical partner (computer or robot) was strictly dependent on the perceived reliability of the mechanical agent itself. On the other hand, the explicit expression of susceptibility towards a human partner was not fully explained by the perceived relative ability of the two interacting partners, suggesting the emergence of inherently social, normative dynamics in peer interaction.
Fig. 5. Scatter plot of individual average trust as a function of the difference between self and partner rating of estimation accuracy, assessed at the end of the Individual trust task. The two measures are negatively correlated in Computer and Robot conditions, whereas they are not correlated in the Human condition.

Discussion

Trust is an essential component of human-human and human-automation interaction. Decades of behavioral research have shown that trust among humans heavily depends on relational and normative mechanisms. On the contrary, large part of the research in human-machine and human-robot interaction in automation focused on the “capacity” dimension of trust, which is grounded in concepts such as performance and reliability. Nevertheless, very few studies specifically investigated similarities and differences in the trust-related dynamics underlying human-human, human-machine and human-robot interaction. This theme is particularly important if we analyze trust within uncertain environments where we do not have access to precise feedback on the performance of our interacting partner(s). In this context, our prior beliefs on the capabilities and relational properties of other agents can bias our interpretation of their behavior and our willingness to trust them. In the current study, we introduced a novel experimental paradigm that allowed us to explore trust towards interacting partners of different natures (human, robot or computer) in two functional, perceptual tasks.

Participants were assigned to three between-subject experimental conditions (Computer, Robot and Human). The first task (Perceptual inference task) was identical for participants in all the conditions, who had to estimate the length of visual stimuli. Participants’ estimates suffered from typical distortions arising from repetition of the perceptual estimation process (i.e., central tendency and scalar variability). Participants’ estimation error was comparable across experimental groups.

In the Individual trust task, participants in the tree conditions believed to perform the task with different partners (a computerized agent, a humanoid robot and a human participant, respectively). Participants made perceptual estimates as in the previous task but could also observe the estimate of their respective partner. In fact, the estimates
of the interacting partners were systematically controlled and identical across conditions. Then participants were asked to make a final decision, selecting a position between the two responses. The shift from their one estimate towards that of the partner (divided by the distance between participants’ and partner’s estimates) has been used as an index of trust, where 0 expresses full trust in own responses and 1 full trust in the partner’s ones. Result reveal that, in all groups, participants did not realize that their accuracy was markedly lower than their partner’s one: the average level of trust was indeed lower than 0.5 (Computer: 0.26; Robot: 0.35, Human: 0.23). This pattern was confirmed by performance ratings collected at the end of the experiment, revealing higher ratings for own accuracy compared to that of the partner, independently of experimental condition. One the one hand, this finding reveals that our task posed marked challenges in the meta-cognitive processes related to the estimation of own and others’ performance. On the other hand, it highlights the existence of egocentric (Yaniv, 2004; Yaniv & Kleinberger, 2000) and self-serving (Duval & Silvia, 2002; Kaniarasu et al., 2014; Sedikides et al., 1998) biases in the process of weighting of own and others’ perceptual capabilities in interacting contexts, for all the types of interacting partners (computer, robot or human).

Nevertheless, we found a significant effect of condition in the actual level of trust expressed by participants towards their partner. In particular, participants in the Robot condition showed significantly higher trust than those in the other two conditions, although the actual accuracy of the interacting partners was identical across conditions. This finding highlights the importance of prior beliefs about the nature and the capabilities of other agents (algorithmic, robotic or human) in determining trust in them (Xu & Dudek, 2016). Several factors, in principle, might have determined this result in our experimental paradigm.

The first question concerns the drivers of the difference between the Robot and the Human condition, which might involve trust mechanisms related to 1) attribution of competence to the partner and 2) normative and social mechanisms modulating the overt expression of trust towards the partner. The first dimension concerns the impact of prior beliefs about the accuracy of the perceptual and motor systems sustaining the partner’s response. In this regard, we highlight that participants in the Robot condition had a brief experience of the existence of a perceptual system in the humanoid robot iCub before starting the experiment. In particular, through a brief meeting with iCub, participants were implicitly informed about the task-related capabilities of the robot. Indeed, participants had the impression that iCub was capable of making autonomous and accurate movements in order to reach and touch a touch-screen placed in front of it. Moreover, participants understood that iCub was endowed with visual perception and was indeed able to see the visual stimuli shown on the tablet. We stress that, in this preliminary encounter with the robot, participants did not receive any direct or indirect clue about the actual capabilities of the robot in terms of estimation accuracy. Indeed, we believe that the higher levels of trust observed in the Robot condition are grounded in the relatively high “a priori” trust that humans genuinely show towards robotic systems (Kaniarasu et al., 2013), which can be maintained in absence of feedback revealing failures or inefficient behavior (Salomon et al., 2018).
Concerning the Human condition, it is likely that participants assumed that they and their human partner possessed very similar perceptual skills; moreover, they were told that they performed the task using identical experimental settings. However, the well-known phenomena of central tendency (Hollingworth, 1910, Jazayeri & Shadlen 2010) and scalar variability (Petzschner et al., 2015) led to marked distortions in participants’ responses and to visible discrepancy between their own responses and those of the partner. In this context, the observed inability to assess own and other’s performance, reinforced by the typical tendency to over-estimate own capabilities in social contexts, led to low trust in the perceptual abilities of the partner. Therefore, most of the participants decided to rely heavily on their own judgments and to take into low consideration those of the partner.

The second dimension that could have an impact on participants’ trust concerns the willingness to overtly and explicitly express a lack of trust in the partner. In this regard, we underline that, in the Individual trust task, participants were told that their partner would observe their final decisions. Extensive evidence in the human-human interaction literature has demonstrated that the overt expression of opinions and judgments in social contexts is modulated by normative conformity and peer pressure (Asch, 1951; Cialdini & Goldstein, 2004; Claidière & Whiten, 2012; Fehr & Schurtenberger, 2018; Pryor et al., 2019), which distort the process of weighting of information provided by others depending on its reliability. This interpretation is corroborated by results of the Individual trust task, showing no between-subject relationship between performance ratings (self – other) and average trust in the Human condition; conversely we found a strong relationship between performance ratings and average trust in the Computer and Robot condition. Moreover, within-subject modulation of trial-by-trial trust based on the current distance from the partner’s response was much less pronounced in the Human condition than in the other two experimental conditions. These findings reveal that participants’ belief of interacting with another human participant interfered in a peculiar way with the process of weighting of information by reliability. In particular, participants might have decided to grant a fair level of trust in the partner even when their responses were inconsistent between each other, following normative principles. Conversely, in Robot and Computer conditions participants’ trust rapidly and monotonically decreased as long as the distance from the partner increased, highlighting a more systematic trust-related decision process based on the evaluation of the partner’s current accuracy. This is consistent with extensive evidence revealing the importance of the “capacity” dimension of trust in human-machine and human-robot interaction (Billings et al 2012; Hancock et al., 2011; van den Brule et al., 2014; Wright et al., 2019).

However, one may ask why, in the presence of normative mechanisms, participants in the Human condition showed a so low general level of trust in their partner. In fact, social norms generally push individuals to grant more trust, or conform more, to peers in order to affiliate with them and control their moral reputation. We may hypothesize that participants would have shown even lower levels of trust in the partner if they had based exclusively on capacity considerations. Future studies may manipulate the possibility for interacting partners to access specific types of information: for instance, participants could be informed that their partner cannot observe their final decisions. In
this context, we should expect a decrease in participants’ trust due to the impossibility to convey anti-social signals to the partner.

An interesting question is whether normative consideration could have played a role also in the Robot condition. Indeed, the human-like and social characteristics of the humanoid robot iCub might have led participants to try to please the robot by showing (relatively) higher levels of trust. This hypothesis is motivated by studies showing that humanoid robots can evoke automatic behavioural reactions similar to those exerted by humans (Sciutti et al., 2015). Indeed, actions of both humanoid robots and humans trigger, in an observer, similar responses in terms of motor resonance (Liepelt et al., 2010; Oztop et al., 2005), anticipation (Sciutti et al., 2013a) and speed adaptation (Sciutti, et al., 2013b) in simple action observation tasks. Most importantly, extensive evidence has revealed the emergence of pro-social behavior towards robots in adults (Connolly et al., 2020; Kühnlenz et al., 2018; Oliveira et al., 2021; Siegel et al., 2009) and children (Beran et al., 2011; Chernyak & Gar, 2016; Martin et al., 2020; Zaga et al., 2017).

However, we lack evidence showing that robots can exert purely normative conformity in humans while expressing judgments or performing tasks in mixed (human-robot) dyads or groups (Vollmer et al., 2018; Brandstetter et al., 2014; Hertz and Wiese, 2016; Shiomi & Hagita, 2016). Moreover, recent evidence has shown that humans’ willingness to trust or imitate robots’ behavior is tightly related with the uncertainty of the task solution (Hertz and Wiese, 2016). Future studies may try to control and manipulate task difficulty and participants’ uncertainty endogenous and exogenous uncertainty underlying the behavior of participants and robotic partner in order to understand the circumstances under which individuals may be more willing to trust robotic partners. Furthermore, future studies may enrich the investigation of human-robot trust by allowing robots themselves to express their own level of trust in the human partner, in line with recent cognitive architectures modelling trust from a robot-centered perspective (Vinanzi et al., 2019, 2021). These dynamics may indeed reveal as crucial in the design of robotic agents that could effectively act as collaborative companions in contexts such as healthcare (Robinson et al., 2014), rehabilitation (Kellmeyer et al., 2018), elderly people assistance (Frennert et al., 2013) and education (Basoeki et al., 2013; Belpaeme et al., 2018).

Concerning the Computer condition, it is unlikely that mechanisms related to the attribution of perceptual–motor competence and social norms played a role in the modulation of trust in the partner. In fact, the computer partner did not possess any kind of perceptual or motor system and could not react emotionally to participants’ lack of trust. We believe that participants’ trust in the Computer condition depended entirely on the estimated performance of the algorithm that produced the perceptual estimates. In this regard, since participants decreased their level of trust as the distance from the partner’s estimate increased, we hypothesize that participants believed that the partner’s accuracy has been varying according to a certain response function. Due to the observed scarce self-assessment of own and partner’s accuracy and consequent egocentric bias, the general average level of trust in the Computer condition was rather low and, interestingly, significantly lower than that the one observed in the Robot condition.
The current study aimed at exploring the differences and the similarities underlying trust in human-human, human-robot and human-computer interaction using a unique and controllable experimental protocol. Our findings offer novel insights in the understanding of the informational and normative mechanisms underlying trust towards peers and autonomous agents.

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Author contributions
J.Z., A.S. and A.F. designed the experimental protocol. J.Z and A.F. programmed the experimental tasks. J.Z. and A.F. collected the data. J.Z. carried out the data analysis. J.Z and A.S. wrote the manuscript. A.F. provided suggestions for improving the manuscript.

Competing interests
The authors declare no competing interests.
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Supplementary information

We report the details of the models ran in the present work. For mixed-effects models, the intercept was allowed to vary across participants including random effects at subject level. In every model equation, $\beta$ expresses coefficients of fixed effects, while $u$ indicates random effects. In the fixed-effect results, $B$ express unstandardized regression coefficients, whereas $\beta$ indicates standardized regression coefficients. Categorical factors (experimental group, 3 levels) have been treated as dummy variables.

Individual trust task

Model 1. Effect of experimental condition on participants’ trust

We tested the effect of experimental condition ($Computer$, $Robot$, $Human$) on participants’ trust, which was computed as the distance between the participants’ final and initial response divided by the distance between the two agents’ initial estimates. We used the following regression model:

$$T = \beta_0 + \beta_1 c + \varepsilon$$

$T$ is the participant’s mean trust in the partner and $c$ is the experimental condition. The $Robot$ condition is the reference category in the model output.

Results:

| Condition       | Mean trust | B ($\beta$) | Std. Err. | t    | p    | 95% Conf. Inter. |
|-----------------|------------|-------------|-----------|------|------|------------------|
| Computer – Robot| - 0.084 (0.562) | 0.041       | - 2.08    | 0.041| - 0.165 | - 0.003          |
| Human – Robot   | - 0.118 (- 0.786) | 0.041       | - 2.91    | 0.005| - 0.198 | - 0.037          |

N. obs 75

There was no difference between the $Human$ and the $Computer$ conditions ($Human – Computer$, $B = - 0.034 (- 0.224)$, $SE = 0.041$, $z = - 0.83$, $p = 0.410$, 95% CI = [- 0.114, 0.047]).
Model 2. Effect of experimental condition on participants’ trust, controlling for estimation error

We ran the previous model (1) adding participants’ mean estimation error (distance between participant’s response and correct response (cm) / stimulus length (cm)), as control variable. We used the following regression model:

\[ T = \beta_0 + \beta_1 c + \beta_2 e + \varepsilon \]

T is the participant’s mean trust, c is the experimental condition and e the (mean) estimation error. The Robot condition is the reference category in the model output.

Results:

| Condition                      | Mean trust | B (\(\beta\)) | Std. Err. | t    | p     | 95% Conf. Inter. |
|--------------------------------|------------|----------------|-----------|------|-------|------------------|
| Computer – Robot               | - 0.081 (0.540) | 0.040         | - 2.01   | 0.048 | - 0.161 | - 0.001          |
| Human – Robot                  | - 0.113 (- 0.754) | 0.040       | - 2.80   | 0.007 | - 0.193 | - 0.032          |
| Estimation error (Robot)       | - 0.330 (- 0.155) | 0.236       | - 1.40   | 0.166 | - 0.801 | 0.140            |

There was no difference between the Human and the Computer conditions (Human – Computer, B = - 0.032 (- 0.213), SE = 0.040, z = - 0.79, p = 0.43, 95 % CI = [- 0.112, 0.048]).

Model 3. Effect of response distance and experimental condition on participants’ trust

We tested the effect of the distance between the participant’s estimate and the partner’s one on trial-by-trial trust, depending on the experimental condition (Computer, Robot, Human). We used the following mixed-effects linear model:

\[ T = \beta_0 + \beta_1 c + \beta_2 d + \beta_3 c \times d + u_0 + \varepsilon \]

T is the participant’s trust in the partner, c is the experimental condition and d is the normalized distance between the two partner’ responses (response distance (cm) / stimulus length (cm)). The Computer condition is the reference category in the model output.

Results:
| Condition              | B (β)     | Std. Err. | z    | p     | 95% Conf. Inter. |
|------------------------|-----------|-----------|------|-------|-----------------|
| Robot – Computer       | 0.047 (0.321) | 0.040 | 1.16 | 0.244 | -0.032 - 0.127  |
| Human – Computer       | -0.125 (-0.140) | 0.041 | -3.08| 0.002 | -0.204 - 0.045  |
| Distance (Computer)    | -0.435 (-0.291) | 0.034 | -12.86| < 0.001 | -0.502 - 0.369 |
| Group*Distance         |           |           |      |       |                 |
| Robot - Computer       | 0.136 (0.091) | 0.046 | 2.99 | 0.003 | 0.047 - 0.226   |
| Human – Computer       | 0.023 (0.252) | 0.045 | 8.40 | < 0.001 | 0.289 - 0.465  |

Results show a negative effect of distance also in Robot and Human conditions: (Robot: B = -0.299 (0.200), SE = 0.031, z = -9.76, p < 0.001, 95 % CI = [-0.359, -0.239]; Human: B = -0.058 (-0.039), SE = 0.029, z = -1.98, p = 0.048, 95 % CI = [-0.116, -0.001]). Moreover, the effect of distance was stronger in the Robot than in the Human condition (Human - Robot, B = 0.241 (0.161), SE = 0.042, z = 5.66, p < 0.001, 95 % CI = [-0.157, 0.324]).