Illusions of Confidence in Artificial Systems

Clara Colombatto[1]* & Stephen M. Fleming[1,2,3]

[1] Department of Experimental Psychology, University College London

[2] Max Planck UCL Centre for Computational Psychiatry and Ageing Research

[3] Wellcome Centre for Human Neuroimaging, University College London

* Correspondence to c.colombatto@ucl.ac.uk

Running Head: Perceiving Confidence

Keywords: Metacognition; Confidence; Artificial Intelligence; Perceptual Decision-Making; Advice Taking

OSF Repository: https://osf.io/8tphs/?view_only=3d3b5cecb629486a9ace79f9be6d558d

Word Count: 7994 (Main Text)

Version: 9/28/23 — Submitted Draft

Abstract

To effectively communicate and collaborate with others, we must monitor not only other people's cognitive states (e.g., what someone thinks or believes), but also their metacognitive states (e.g., how confident they are in their beliefs). Confidence is however rarely communicated explicitly: instead, we often perceive others' confidence via implicit signals such as speech prosody or movement dynamics. Recent advances in artificial intelligence (AI) have broadened the scope of these metacognitive inferences: artificial agents often perform similarly to humans yet rarely explicitly signal their confidence in their beliefs, raising the question as to how humans attribute confidence to AI. Here we report five pre-registered experiments in which participants observed human and artificial agents make perceptual choices, and reported how confident they thought the observed agent was in each choice. Overall, attributions of confidence were sensitive to observed variables such as task difficulty, accuracy, and response time. Strikingly, participants attributed higher confidence to AI agents compared to other humans, even though their behaviour was identical. An illusion of greater confidence in artificial agents' decisions generalised across different behavioural profiles (Experiment 2), agent descriptions (Experiment 3), and choice domains (Experiment 4). Attributions of confidence also influenced advice-taking behaviour, as participants were more willing to accept the advice of artificial systems compared to matched humans (Experiment 5). Overall, our results uncover a systematic illusion of confidence in AI decisions, and highlight the importance of metacognition in guiding human-machine interactions.

Significance Statement

Artificial intelligence is increasingly pervasive in our daily lives, making the study of human-machine interactions a key challenge for cognitive science. Perceptions of machine confidence are likely to play a key role in how we interact and collaborate with artificial systems, and yet little is known about how we attribute confidence to AI algorithms. Here we show that when watching other agents make decisions, people consistently overestimate the confidence of artificial agents compared to other humans, even when their behaviour is identical. Perceived confidence also affected advice-taking and perceived trustworthiness. Taken together, these results uncover a powerful illusion of confidence in artificial systems and highlight a central role for metacognition in human-machine interactions.

Autonomous systems are increasingly pervasive in our daily lives – from personal assistance and product suggestions to healthcare recommendations and automated transportation. As artificial intelligence (AI) becomes progressively advanced and ubiquitous, key questions arise regarding how humans interact with machines. For example, building more optimal recommendation algorithms is useful only insofar as humans are willing to trust their suggestions, and designing more skilled robots is useful only insofar as humans are willing to rely on their assistance. Technological advances must thus be complemented with a psychology of human-machine collaboration – a novel challenge for cognitive science [1].

The study of human-machine interactions may be especially pressing given that they might involve different processes compared to human-human interactions [2]. For example, past work has shown that humans hesitate to rely on advice or help from algorithms, even when they perform equally well if not better than humans – a phenomenon known as 'algorithm aversion' ([3-4]; for a review, see [5]; c.f. [6]). And while attitudes towards AI can be enhanced by factors such as affective abilities [7], physical presence [8], or decision interpretability [9], a prior belief about actions being generated by computers (vs. humans) can be sufficient to influence perceptions of otherwise identical behaviours [10-11].

One striking difference between human-human and human-machine interactions is that when we make decisions with other people, we have access not only to their behaviour but also to their metacognitive states – for instance, how confident they are in a belief or decision (for a review, see [12]). In humans, such confidence can be revealed not only explicitly, via verbal estimates (e.g. [13]) or risk preferences (e.g. [14]), but also implicitly via response times [15-17], movement dynamics [18], and speech prosody [19-20]. In other words, humans regularly *infer* or *attribute* confidence to each other by tracking implicit signatures of metacognition. This type of information is highly valuable in collaborative decision-making [21]: for example, it helps resolve disagreements among group members [22], and indeed group decisions are more effective than individual ones only when confidence estimates are shared [23].

If attributions of metacognition are key to human-human collaboration, they should also be central to human-machine interactions. However, little is currently known about how humans attribute metacognition and confidence to AI systems. In fact, this type of inference is difficult when interacting with machines which are typically designed to fulfil first-order rather than metacognitive functions, and often do not carry outward signs of confidence in their internal processes (although see [24-27]). In fact, AI's capacity for metacognition is developing and will likely differ from humans' [28]. For example, while in humans confidence typically decreases as tasks get harder, some models show the opposite pattern of results [29]. Here we thus set out to investigate attributions of metacognition to humans and machines, and whether such attributions affect impressions of trust and competence.

To investigate attributions of metacognition, we designed a paradigm where participants watched other agents make perceptual choices and were asked to determine how confident the agents were in their choices. This key dependent measure thus involves participants' estimates of others' confidence, as opposed to estimates of others' actual performance (e.g. [30]), or participants' own confidence in others' choices (e.g. [31]). This design allowed us to investigate how attributions of confidence are modulated by decision variables such as task difficulty, observed accuracy, and observed response time. At the same time, we kept these overall behaviours constant across different agents and varied the nature of the agents making the choices – which allowed us to examine how attributions of metacognitive states can depend on prior beliefs about agency, even when actual performance was in fact identical.

To pre-empt our results, we found a robust illusion of confidence in AI systems, despite observed behaviour being identical to matched human agents, and despite attributions of metacognition in both cases being governed by similar factors. In additional experiments, we tested the robustness and generalisability of these results, examining how confidence is attributed when machines display human-like (Experiment 1) or stereotyped behaviour (Experiment 2), when artificial agents are described in more or less anthropomorphic ways (Experiment 3), and when the task involves a general knowledge quiz (Experiment 4) rather than perceptual judgments. Finally, we explored the impact of perceived confidence on actual behaviour by examining advice-taking in a collaborative decision-making task (Experiment 5). Overall, these results reveal how people perceive metacognition in humans and machines, and demonstrate how even illusory attributions of confidence can have powerful influences on perceived trustworthiness and collaborative behaviour in human-human and human-machine interactions.

Results

Experiment 1: Observing Perceptual Decisions

To investigate how people attribute confidence to others, we designed a task divided into two phases, as illustrated in Figure 1. In the first phase (‘Self’), participants made a series of perceptual decisions – namely, which of two noise patches contained a Gabor stimulus with varying opacity (Fig. 1A). In the second phase (‘Other’), participants watched other agents make these decisions, with these agents being either another person (Fig. 1B) or a robot (Fig. 1C), presented in a randomised order. The behaviour of these agents (namely, accuracy and response times) was determined by the behaviour of one of 20 real “counterpart participants” who had previously taken part in the experiment (for details, see Methods and Materials). Importantly, each participant was matched with one counterpart participant, whose performance determined the behaviour of both agents seen by the participant in the ‘Other’ phase. The same behavioural parameters and generative functions thus determined the behaviour of both the other person and the robot, such that within each participant performance was equated across the two agents. We hypothesised that estimates of other agents’ confidence would depend on the difficulty of the task, but also on their behaviour (namely, accuracy and response times), as well as on their nature (human vs. artificial). All analyses reported here were pre-registered unless noted otherwise.

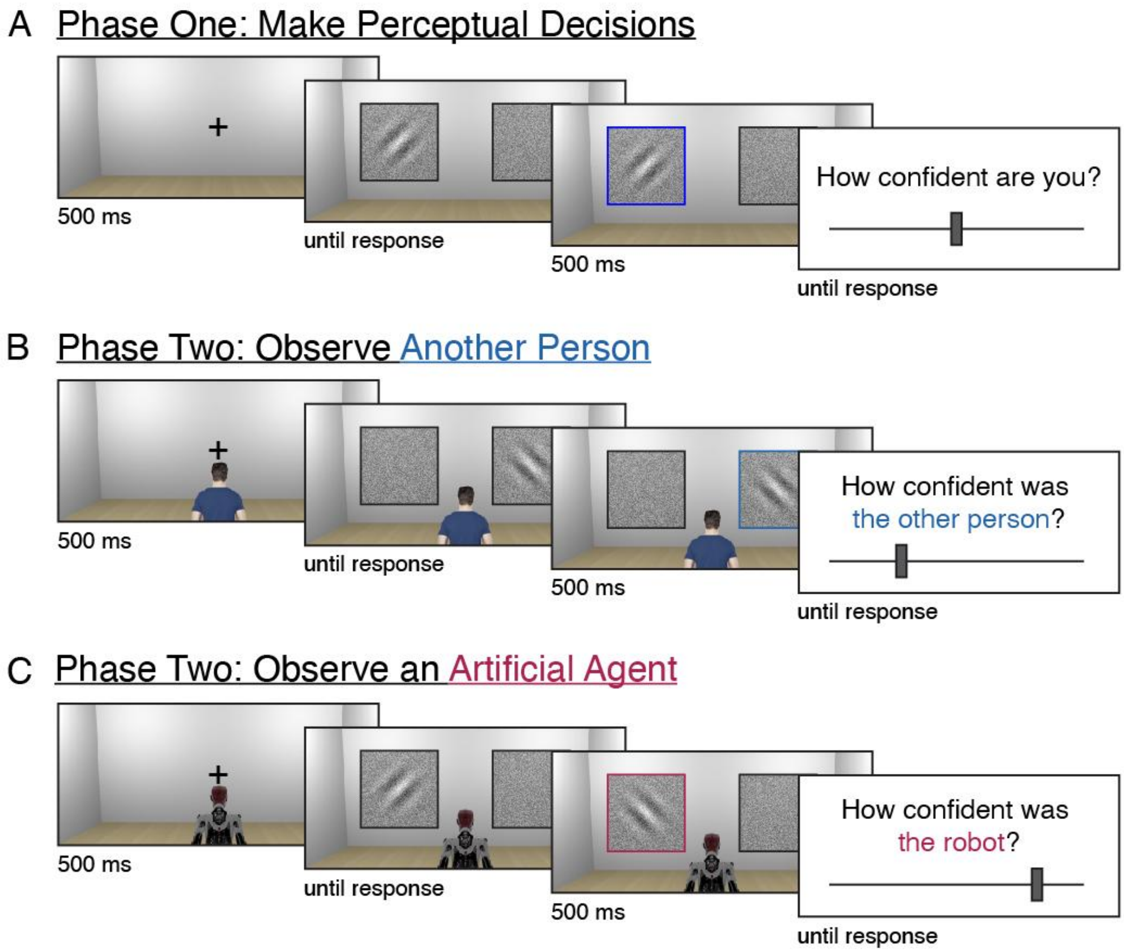

Figure 1. Overview of Design for Experiment 1. (A) Participants first completed a perceptual decision-making task where they selected which of two stimuli contained a Gabor patch (Phase One; 'Self'). (B and C) Next, participants observed other agents complete the same task, and reported their perception of the other agent's confidence (Phase Two; 'Other'). The other agent was described and depicted as either another person (B) or a robot (C), although their actual performance on the task was identical.

Cues to Others' Confidence

Attributions of confidence were sensitive to task parameters (i.e., task difficulty) as well as observed performance (i.e., accuracy and response times). As predicted, participants attributed higher confidence on easier trials where the target was presented at higher contrast (main effect of task difficulty: B=0.54, SE=0.14, t(19777)=3.70, p<.001, CI=[0.25, 0.82]). Confidence estimates were also higher on trials where the agent responded faster (main effect of observed response time: B=-9.89, SE=0.31, t(19729)=-32.31, p<.001, CI=[-10.49, -9.29]; Fig. 2A), and on trials where the agent responded accurately (mean=55.31, SE=1.16) vs. inaccurately (mean=44.59, SE=1.19; main effect of observed accuracy: B=12.27, SE=0.91, t(19788)=13.51, p<.001, CI=[10.49, 14.05]). Interestingly, this effect was also sensitive to task difficulty: there was an interaction between observed accuracy and task difficulty (B=2.61, SE=0.29, t(19783)=8.97, p<.001, CI=[2.04, 3.18]; Fig. 2B) wherein easier trials generated higher confidence estimates when the agent was correct (slope=1.85, SE=0.06, CI=[1.73, 1.97]), but not when the agent was incorrect (slope=-0.63, SE=0.11, CI=[-0.84, -0.41]). This effect mirrors a classic statistical signature of confidence, the folded X pattern [32-33], suggesting that people have a sophisticated understanding of the factors affecting others' confidence.

We also investigated a possible relationship between self-directed and other-directed metacognition. We operationalised self-directed metacognition as metacognitive efficiency as participants were completing the detection task in Phase One, and other-directed metacognition as the granularity of their attributions for other agents in the observation in Phase Two. Contrary to our hypothesis, there was no correlation between participants' metacognitive efficiency and their capacity for other-directed metacognition (r(111)=-0.06, p=.556).

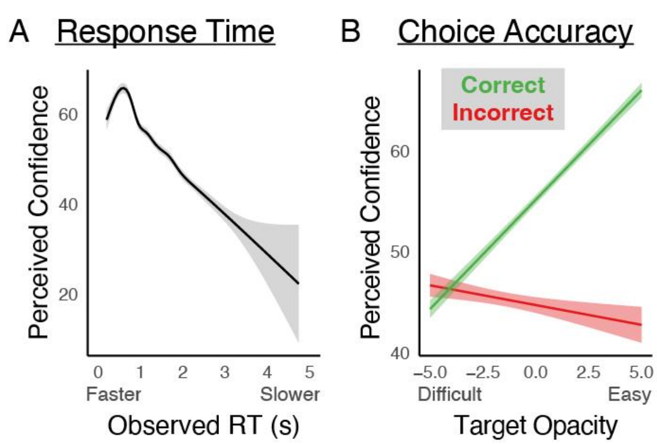

Figure 2. Evaluating Others' Confidence. (A) Inferred confidence was affected by observed response time, with higher confidence inferences on trials where the agent responded faster. (B) Inferred confidence was generally higher for easier trials, but only when the agent was accurate (green) and not when inaccurate (red). These data are from Experiment 1, but these patterns were robust across all experiments. Error bands represent 95% confidence intervals.

Confidence in Humans versus Machines

We next turned to our key question of whether and how attributions of confidence differed between humans and machines. Strikingly, perceived confidence was higher for robots (mean=54.18, SE=1.12) vs. other people (mean=45.65, SE=1.12), despite their performance being identical (main effect of agent: B=11.82, SE=0.88, t(19763)=13.41, p<.001, CI=[10.09, 13.54]; Fig. 3A). This effect of agent also interacted with the main effects of difficulty (B=-0.82, SE=0.28, t(19764)=-2.91, p=.004, CI=[-1.38, -0.27]) and with observed response time (B=-2.30, SE=0.56, t(19763)=-4.09, p<.001, CI=[-3.40, -1.20]), in that difficulty had a stronger effect on perceived confidence when the attribution was about another person (difficulty slope for other person=0.78, SE=0.09, CI=[0.61, 0.95], slope for robot=0.43, SE=0.09, CI=[0.26, 0.60]), while response time had a stronger effect on perceived confidence when the attribution was about the robot (response time slope for other person=-8.83, SE=0.42, CI=[-9.65, -8.02], for robot=-11.13, SE=0.41, CI=[-11.93, -10.33]). Taken together, these analyses show that participants attributed greater confidence to the robot, despite the agents having identical performance – an 'illusion of confidence' in AI.

Mechanisms of Confidence Attribution

To further deconstruct the relative contribution of observed behaviour and prior beliefs about the agents to confidence attributions, in an additional exploratory analysis we investigated how confidence attributions on a given trial were affected by observations on previous trials (Fig. 3B). We found that confidence attributions on a given trial were influenced by the type of agent and their behaviour on the current trial (main effect of agent, accuracy, difficulty, response time, accuracy × difficulty interaction: all ps<.001; Fig. 3B, left), but also by their behaviour on previous trials. This was especially true for previous response times (all ps<.006), and less so for the interaction between accuracy and difficulty (ps=.386, .094, .968, .029, and .226; Fig. 3B, middle). The strongest predictors of confidence attributions however were previous confidence attributions, which leaked into the current trial (all ps<.001; Fig. 3B, right). This suggests that while attributions of confidence are sensitive to observed behaviour, they are also influenced by longer-timescale fluctuations, consistent with previously reported empirical patterns in self-directed metacognitive judgments [34-35]. This confidence leak phenomenon was also similar when interacting with both human and AI agents, as the impact of all variables from previous trials did not interact with agent type (all ps>.095, except for the accuracy x difficulty interaction on the third and fourth previous trials being stronger for the robot vs. the human, ps=.037 and .058). This suggests that attributions of confidence are sophisticated, in that they show integration over time similar to that observed for self-directed metacognition, but they are also biased, in that they are systematically higher for robots irrespective of both current and recent observed behaviour.

In addition, we sought to further characterise this illusion of confidence by exploring its timecourse across trials, i.e. as participants observe the agents make their choices (Fig. 3C). We found that in general, attributions of confidence became lower over the course of the block (main effect of trial number: $B=-0.36$, $SE=0.07$, $t(19769)=-5.14$, $p<.001$, CI=[-0.50, -0.22]), with an illusion of confidence in AI being strongest at the beginning of the relevant experimental blocks (interaction between trial number and agent: $B=-1.09$, $SE=0.14$, $t(19769)=-7.80$, $p<.001$, CI=[-1.36, -0.81]). This learning effect was especially strong for participants who observed another person before the robot (three-way interaction between trial number, agent, and block order: $B=1.40$, $SE=0.22$, $t(19769)=6.39$, $p<.001$, CI=[0.97, 1.82]), suggesting that participants had an expectation that the robot would be more confident, especially immediately after watching the other person perform the task. Indeed, the effects of both trial number and agent were stronger for participants who watched the other person first (two-way interaction between trial number and block order: $B=0.34$, $SE=0.11$, $t(19769)=3.12$, $p=.002$, CI=[0.13, 0.56]; between agent and block order: $B=-11.60$, $SE=1.48$, $t(19769)=-7.83$, $p<.001$, CI=[-14.51, -8.70]). Together, these results suggest that while participants were sensitive to observed behaviour, they also had a strong prior belief that machines would be more confident, especially after having observed humans first.

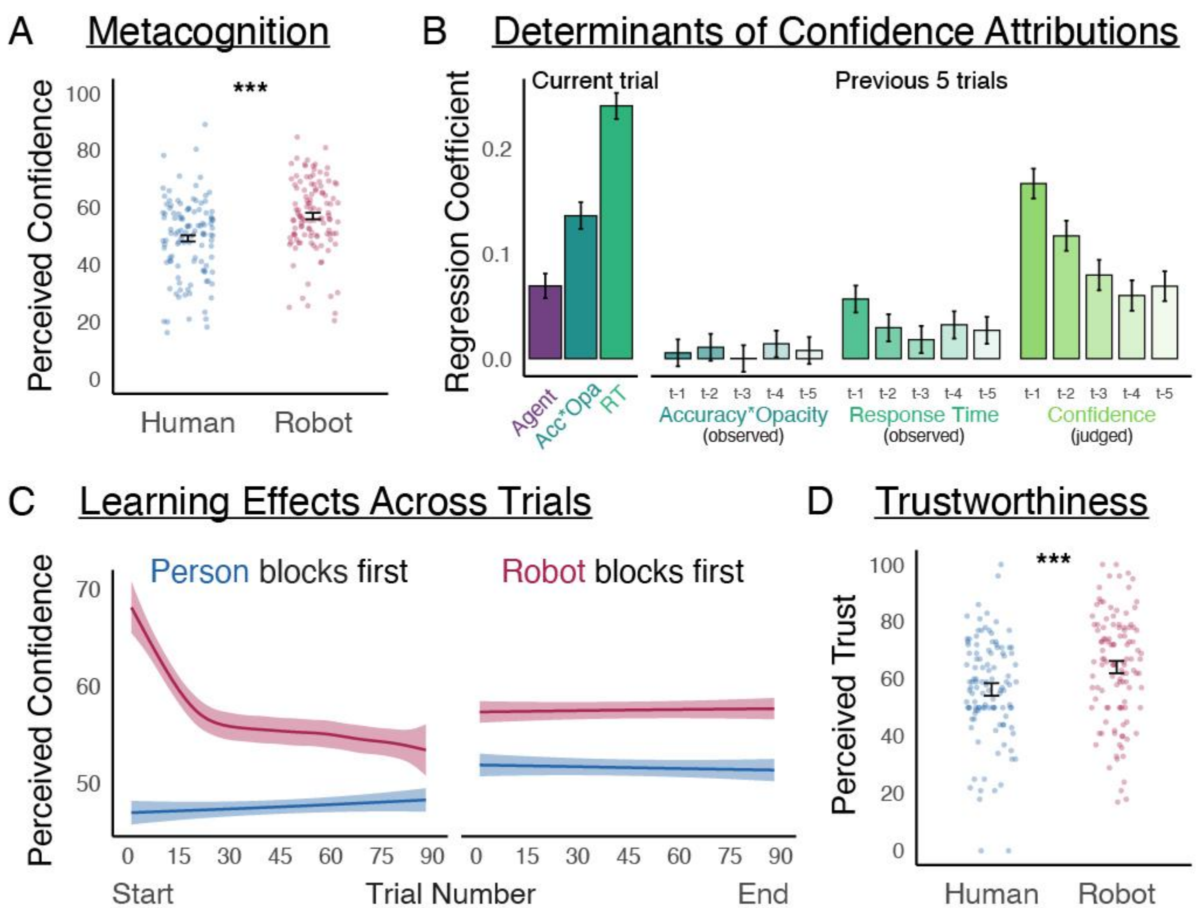

Figure 3. Attributions of Confidence in Humans and AI in Experiment 1. (A) Judgments of perceived confidence were higher for the artificial agent (red) compared to the human agent (blue). (B) In addition to agent (purple), these attributions were also predicted by behaviour observed on the current trial (left), as well as by confidence estimates on the previous trials (right). (C) The difference between agents was robust across experimental trials, and was especially strong at the beginning of the experiment for people who observed the other person first and the artificial agent later. (D) Perceived trustworthiness was also higher for robots compared to other people. Error bars correspond to mean ± 95% confidence intervals, for A and D also subtracting out the shared variance***p<.001.

From Perceived Confidence to Social Impressions

At the end of the experiment, we also asked participants to evaluate the agents' trustworthiness and competence (for details, see Methods and Materials). As depicted in Figure 3D, the artificial agent was rated as more trustworthy than the other person ($t(112)=3.51$, $p<.001$, d=0.33, CI=[0.14, 0.52]). The artificial agent was also rated as more competent, despite having identical performance to the human counterpart ($t(112)=7.46$, $p<.001$, $d=0.70$, CI=[0.49, 0.91]). These higher-level social impressions thus mirror the higher attributions of confidence – and indeed, an additional exploratory analysis revealed that attributions of confidence were positively correlated with both trustworthiness ($r(224)=0.23$, $p<.001$) and competence ($r(224)=0.26$, $p<.001$). This suggests that attributions of metacognition are related to the formation of broader personality impressions, even for artificial systems.

Experiment 2: Machine-like Behaviour

The results of Experiment 1 show that people form estimates of other agents' confidence guided by a sophisticated model of their behaviour, but that these attributions are consistently inflated for artificial agents. In Experiment 1, however, the behaviour of both agents was human-like, with accuracy and response times derived from the actual behaviour of "counterpart participants" who had previously taken part in the study. In Experiment 2, we sought to test the robustness of this illusion of confidence in AI by investigating whether it also arises when observing stereotyped, machine-like behaviour. This experiment was identical to Experiment 1, except that accuracy at each difficulty level was now based on the accuracy of a neural network trained to complete the perceptual discrimination task, and observed response times were now faster and less variable (for details, see Methods and Materials). As in Experiment 1, these generative functions were kept constant across both machine and human agents.

As in Experiment 1, we found main effects of difficulty ($B=0.98$, $SE=0.07$, $t(19074)=13.28$, $p<.001$, CI=[0.83, 1.12]) and accuracy ($B=8.97$, $SE=0.45$, $t(19076)=19.82$, $p<.001$, CI=[8.08, 9.85]), as well as an interaction between these factors ($B=2.51$, $SE=0.15$, $t(19076)=17.04$, $p<.001$, CI=[2.22, 2.80]) wherein easier trials generated higher confidence estimates when the agent was correct (slope=2.23, SE=0.07, CI=[2.10, 2.36]), but not when the agent was incorrect (slope=-0.28, SE=0.13, CI=[-0.54, -0.02]). Most importantly, we again observed a main effect of agent ($B=12.07$, $SE=0.44$, $t(19070)=27.62$, $p<.001$, CI=[11.21, 12.93]), with higher perceived confidence for the robot (mean=64.15, SE=1.08) vs. the other person (mean=52.08, SE=1.08; Fig. 4A). Agent type again interacted with difficulty ($B=-0.68$, $SE=0.14$, $t(19070)=-4.76$, $p<.001$, CI=[-0.96, -0.40]), with a stronger relationship between difficulty and perceived confidence for the other person (slope=1.32, SE=0.10, CI=[1.13, 1.52]) compared to the robot (slope=0.64, SE=0.10, CI=[0.45, 0.84]).

We also replicated the (now pre-registered) effect of trial order, with stronger differences in the effect of agent at the beginning of each block, especially for participants who watched the other person before the robot (three-way interaction between trial number, agent, and block order: B=1.64, SE=0.22, t(19069)=7.36, p<.001, CI=[1.20, 2.08]). Higher-level social impressions were again more positive for the robot, who was perceived as more trustworthy (t(108)=4.26, p<.001, d=0.41, CI=[0.21, 0.60]) and more competent (t(108)=6.67, p<.001, d=0.64, CI=[0.43, 0.84]) – with these traits also being positively correlated with confidence attributions (trustworthiness r(216)=0.32, p<.001; competence r(216)=0.44, p<.001).

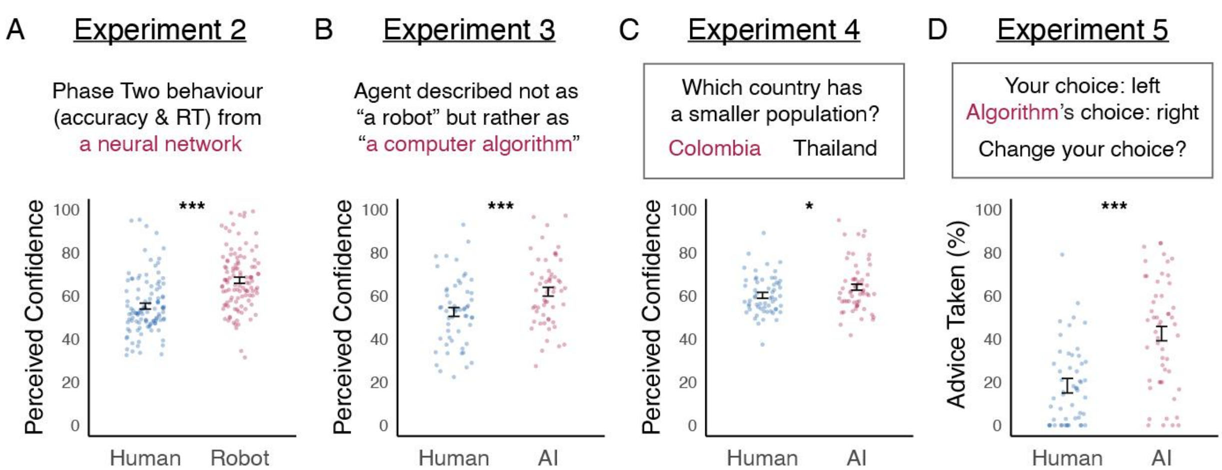

Figure 4. Generalisation Tests for an Illusion of Confidence in AI. For each experiment, we report key manipulations (top) and results (bottom). Perceived confidence was higher for the artificial agent (red) compared to the human agent (blue) across all experiments. *p<.05, ***p<.001.

Experiment 3: Machine-like Descriptions

In both Experiments 1 and 2, the non-human agent was described and depicted as a robot (Fig. 1C). To ensure that attributions of metacognition were not influenced by this anthropomorphic presentation, we conducted a new experiment identical to Experiment 2, but where the agents were no longer explicitly pictured, and the non-human agent was described as a computer algorithm (for details, see Methods and Materials).

The results again replicated Experiments 1 and 2: we found main effects of difficulty (B=1.17, SE=0.11, t(9798)=10.17, p<.001, CI=[0.94, 1.39]) and accuracy (B=14.01, SE=0.71, t(9799)=19.75, p<.001, CI=[12.62, 15.40]), as well as an interaction between these factors

(B=3.67, SE=0.23, t(9799)=15.94, p<.001, CI=[3.22, 4.12]) wherein easier trials generated higher confidence estimates when the agent was correct (slope=3.00, SE=0.10, CI=[2.80, 3.21]), but not when the agent was incorrect (slope=-0.67, SE=0.21, CI=[-1.07, -0.26]). Most importantly, we again observed a main effect of agent (B=8.79, SE=0.70, t(9794)=12.62, p<.001, CI=[7.43, 10.16]), with higher perceived confidence for the AI (mean=56.83, SE=1.83) vs. the other person (mean=48.04, SE=1.83; Fig. 4B). This is particularly striking given that in this design displays of agent behaviour were now identical, with the only difference being whether the agent was labelled as either a human or computer algorithm prior to the observation trials.

We also replicated the interaction between agent and difficulty (B=-0.86, SE=0.23, t(9794)=-3.81, p<.001, CI=[-1.30, -0.42]), as well as the three-way interaction between trial number, agent, and block order (B=1.00, SE=0.36, t(9794)=2.76, p=.006, CI=[0.29, 1.70]). As in Experiments 1-2, the artificial agent was seen as more trustworthy (t(55)=5.13, p<.001, d=0.69, CI=[0.39, 0.97]) and more competent (t(55)=6.22, p<.001, d=0.83, CI=[0.52, 1.13]) – with these traits also being positively correlated with confidence attributions (trustworthiness r(110)=0.34, p<.001; competence r(110)=0.33, p<.001).

Experiment 4: A General Knowledge Task

All experiments reported thus far involved a perceptual decision-making task, with participants deciding (and watching others decide) which of two stimuli contained a Gabor grating. However, past work has shown that attitudes towards algorithms can vary depending on the type of task at hand [7]. To ensure these effects are not specific to tasks involving perception, we investigated a different decision-making domain involving real-world knowledge [32]. Experiment 4 was thus similar to Experiment 3, except that the perceptual task was replaced by a general knowledge task where agents select which of two countries has a larger population ([36]; Fig. 4C; for details, see Methods and Materials).

The results were consistent with all previous Experiments: we obtained main effects of difficulty (B=1.53, SE=0.53, t(10320)=2.92, p=.004, CI=[0.50, 2.56]) and response time (B=-5.92, SE=0.19, t(10324)=-30.69, p<.001, CI=[-6.29, -5.54]) on perceived confidence; we again found an interaction between difficulty and accuracy (B=4.22, SE=1.05, t(10319)=4.03, p<.001, CI=[2.17, 6.27]) wherein easier trials generated higher confidence estimates when the agent was correct (slope=2.71, SE=0.32, CI=[2.09, 3.34]), but not when the agent was incorrect (slope=-1.43, SE=0.52, CI=[-2.45, -0.41]). Most importantly, we again observed a main effect of agent

(B=2.71, SE=1.29, t(10313)=2.10, p=.036, CI=[0.18, 5.24]), with higher perceived confidence for the AI agent (mean=63.15, SE=1.25) vs. the other person (mean=59.12, SE=1.25; Fig. 4C). We also replicated the three-way interaction between trial number, agent, and block order (B=0.81, SE=0.32, t(10319)=2.51, p=.012, CI=[0.18, 1.45]). Finally, the artificial agent was again seen as more trustworthy (t(58)=3.32, p=.002, d=0.43, CI=[0.16, 0.70]) and more competent (t(58)=4.88, p<.001, d=0.63, CI=[0.35, 0.91]) – with these traits also being positively correlated with confidence attributions (trustworthiness r(116)=0.38, p<.001; competence r(116)=0.43, p<.001). These results suggest that even in general knowledge tests, people expect algorithms to be more confident in their answers, despite the algorithm's performance being equivalent to other agents. This shows how the effects uncovered in previous experiments are not specific to perceptual decision-making but rather also arise in general-knowledge domains relevant to real-world decision-making.

Experiment 5: Influences on Advice-Taking

The experiments discussed so far show that people can form estimates of others' confidence across different behavioural profiles, agent descriptions, and task domains. These attributions were however always measured via explicit ratings ("How confident do you think the other person was?"), and it remains unclear whether and how they affect behaviour in more ecologically valid scenarios. For example, effective metacognition is important for guiding advice-taking in joint decision-making [21]: optimal advice integration should weigh our own confidence against others' confidence, such that advice given with low confidence should have a lower impact than advice given with high confidence [14]. To investigate the effect of perceived confidence on advice-taking, we designed a task where participants make perceptual choices, and are then given the opportunity to revise their choice after receiving 'advice' from one of two other agents [37] – either another person or a computer algorithm (Fig. 4D; for details, see Methods and Materials).

Advice-taking behaviour was consistent with the explicit ratings of perceived confidence from previous experiments. When receiving advice that was discordant with their initial choices (36.07% of all trials), participants sometimes reversed their choices (29.51% of discordant trials), and they did so more often when the task was more difficult (main effect of difficulty, B=0.08, SE=0.02, z=5.08, p<.001, CI=[0.05, 0.11]) and when they were initially wrong (main effect of initial accuracy, B=0.99, SE=0.10, z=9.79, p<.001, CI=[0.79, 1.19]). There was also an interaction between difficulty and initial accuracy (B=0.20, SE=0.03, z=6.23, p<.001, CI=[0.14, 0.26]) wherein initial choices were revised more often on more difficult trials when the initial choice was incorrect (slope=0.18, SE=0.02, CI=[0.14, 0.23]), but not when correct (slope=-0.02, SE=0.02, CI=[-0.06, 0.03]). Most importantly, we observed a main effect of agent (B=1.37, SE=0.10, z=13.08, p<.001, CI=[1.16, 1.58]), with a greater number of choice revisions after receiving advice from the AI (mean=1.87, SE=0.20) vs. the other person (mean=0.45, SE=0.19; Fig. 4D). We also replicated the three-way interaction between trial number, agent, and block order (B=0.12, SE=0.05, z=2.37, p=.018, CI=[0.02, 0.22]). Finally, we found similar effects of agent on higher-level social impressions – with the artificial agent being perceived as more trustworthy (t(51)=4.05, p<.001, d=0.56, CI=[0.27, 0.85]) and more competent (t(51)=3.60, p<.001, d=0.50, CI=[0.21, 0.79]), in line with advice taking (trustworthiness r(102)=0.50, p<.001; competence r(102)=0.48, p<.001). This experiment thus showed that participants do not just attribute higher confidence to artificial agents, but are also more willing to defer to their advice as a consequence.

Discussion

Successful cooperation requires an understanding of others' mental states such as their feelings, goals, and beliefs – and indeed much work across all areas of psychology and neuroscience has explored our rich capacity for mental state attributions. Here we consider that in addition to others' *cognitive* states, social interactions also require that we perceive others' *metacognitive* states – namely how confident others are in their beliefs and decisions. Across five experiments, we found that when watching other agents make decisions, people form sophisticated estimates of their confidence, influenced by both task variables (e.g., difficulty) and observed behaviours (e.g., response time). Strikingly, however, people also consistently ascribed higher confidence to the decisions of artificial agents, compared to those of performance-matched humans. This illusion of confidence emerged from both human- and machine-like behaviour (Experiment 2), and from both anthropomorphic and non-anthropomorphic agent descriptions (Experiment 3). Moreover, these effects were consistent across different decision domains (Experiment 4), and also manifested in a setting involving advice-taking (Experiment 5).

The illusion of confidence uncovered in these experiments was especially striking given that in each experiment, the behaviour of the artificial agents was in fact equated to the human agents: the observed accuracy and response times were drawn from the same generative functions, such that any difference in perceived confidence solely reflected participants' assumptions about the agents. Indeed, further analyses of learning effects revealed that this bias was stronger at the beginning of the experimental blocks, and diminished thereafter as participants observed the agents' behaviour — suggesting that it may originate from a generalised prior belief that machine decisions are more confident. However, while this effect was modulated by observation and learning, it was also robust and highly replicable: the illusion of confidence in artificial agents was consistent across different behavioural profiles, arising both when the agents' behaviours were based on actual participants who had previously completed the experiment (Experiments 1, 4, and 5) and when based on a neural network trained to complete the task (Experiments 2 and 3). In addition to its robustness, the illusory boost in confidence for artificial agents was also sensitive to contextual factors, interacting with choice difficulty in Experiments 1 to 3, and with response times in Experiment 1.

Of note, in all Experiments participants reported that the computer algorithm was not just more confident in each choice, but also overall more trustworthy and more competent compared to the matched human counterpart. While future work is needed to probe possible causal relationships between perceived metacognition and social impressions, this result suggests that illusions of confidence may play an important role in human-machine interactions. For example, past work has shown that when making decisions in groups, individuals adapt their own confidence estimates to align with others' [13], raising the possibility that metacognitive processes may be altered when collaborating with humans vs. machines. In addition, an illusion of confidence may play a role in collaborations involving delegation, where human operators can choose to delegate tasks to automated agents [38] and may choose to do so more often if higher confidence is attributed to a potential collaborator. The results of Experiment 5 are especially relevant in this respect, as they suggest that attributions of confidence affect advice taking in a scenario akin to AI support and assistance. In turn, our findings highlight the necessity for developing solutions for artificial metacognition that allow AI agents to appropriately communicate (potentially low) degrees of confidence in their behaviour [39]. Future work could explore types of metacognitive broadcasts (e.g., implicit vs. explicit) to facilitate alignment in human-AI interactions, and how these might help counter inaccurate priors.

More broadly, these investigations demonstrate a rich capacity for metacognitive attributions, introducing a new dimension to social perception and mentalizing. In particular, participants were able to intuitively perceive other agents' metacognitive states based on observed variables that past research on metacognition has shown to affect (self-)confidence. For example, in Experiments 1 and 4 participants used response time as a cue to confidence, with faster response times leading to higher confidence attributions. This result is consistent with past work showing that response times can function as cues not only to confidence [40], but also to mental states including cognitive effort [41], abstract preferences [15, 42], personality traits [43], and moral character [44]. But rather than being parametrically dependent on just one variable, attributions of metacognitive states incorporated several cues as well as their interactions. For example, in all experiments participants used task difficulty as a cue to confidence, with higher confidence attributions for easier trials — but only when the decisions were correct, mirroring a classic statistical signature of confidence [32-33]. Importantly, comparisons with participants' own metacognitive profiles in Experiment 1 confirmed that these attributions did not just reflect participants' own confidence, but truly reflected actual inferences over others' behaviour. This form of 'folk metacognition' adds a new dimension to a growing body of evidence for how we achieve a naïve understanding of higher cognitive processes such as awareness and attention [45-47].

This initial demonstration of our capacity for metacognitive attributions also opens several new avenues for future research. For example, the current tasks involved minimal social interactions, with the other agents being described in relatively anonymous and generic terms (e.g., "another participant who previously completed this task"). However, everyday life more typically involves repeated interactions with known others who may differ in baseline metacognitive abilities, above and beyond the current context. For example, past work has shown robust individual differences in metacognition [48] related to variation in mental health [49] and personality traits such as dogmatism and radicalism [50-51], raising the possibility that perceived confidence might depend not just on temporary states (e.g., how fast someone responds in that instance), but also on knowledge of more general personality traits (e.g., how fast someone responds in that instance compared to how they typically respond in the face of uncertainty).

The types of metacognitive attributions explored in the current study may also have rich connections to our robust capacity for self-directed metacognition [52]. This link was partially explored in Experiment 1: we expected that participants with better metacognitive insight into their performance would also form more fine-grained metacognitive attributions about others, but did not find any significant relationship between these measures. This result is relevant to past work on action understanding, which posits that inferences of others' mental states from their actions are based on observers' own motor system. For example, past work has shown that inferences of others' confidence are relative to participants' own kinematic profiles, likely because these judgments are based on simulations of participants' own motor system [18]. Of course, the current experiments differed from these as participants did not have access to movement kinematics; but they demonstrate that such judgments need not take into account participants' own metacognitive system, and can in principle be made on the basis of perceptual information alone. Future work could probe possible associations and dissociations between self- and other-directed metacognition, and the relative weight given to external cues such as response times [17] and contextual factors and internal models of self and other ([31]; see also [12]). An especially intriguing future direction in this domain is the study of child development, given proposals that metacognition may be scaffolded onto the development of social cognition [53-54].

In sum, these results demonstrate that people can form robust impressions of the metacognitive states of other agents. Beyond demonstrating the effect of candidate cues that affect attributions of metacognition (e.g., response times), we also highlight a striking illusion of confidence when attributing metacognition to AI, even when the actual performance is matched to humans. This metacognitive illusion has significant consequences for human-AI interactions, as countering this bias will require the development of accurate systems for artificial metacognition, and reliable means of communication of metacognitive states with humans. Collectively, our results point to a rich capacity for metacognitive inference from others' behaviour, and highlight the importance of metacognition in social interactions.

Methods and Materials

Participants

For each experiment, participants were recruited via Prolific (prolific.co; [55]) in exchange for monetary compensation. Participants were able to take part in the experiments if they were fluent in English, had a Prolific task approval rate of at least 95%, and had not previously participated in any of the other studies reported here. As per our pre-registered plan, we recruited *N*=120 participants for Experiment 1. This sample size was determined via a power analysis of pilot data (*N*=18) and was fixed for Experiment 2. The sample size for the remaining experiments was halved to *N*=60 based on a power analysis of Experiments 1 and 2. All methods and procedures were approved by the UCL Research Ethics Committee, and all participants provided their informed consent.

Participants were excluded according to our pre-registered plans if they (1) had a viewport size smaller than 720x500px (*N*=1 in Experiment 4); (2) reported having encountered problems (see Debriefing; *N*=2 in Experiment 1, *N*=1 in Experiment 2); (3) failed to answer our open-ended text questions sensibly (see Debriefing; *N*=1 in Experiment 1, *N*=1 in Experiment 5); (4) had a mean accuracy in the catch questions about the agents' confidence lower than 70% for Experiment 5 (*N*=6); and (5) converged on a target with opacity level lower than 5% in Phase 1 (*N*=4, 10, 4, 1; in Experiments 1, 2, 3, and 5, respectively). The final sample sizes were thus *N*=113 in Experiment 1 (26 females, M_{age}=31.65), *N*=109 in Experiment 2 (32 females, M_{age}=33.76), *N*=56 in Experiment 3 (25 females, M_{age}=33.07), *N*=59 in Experiment 4 (24 females, M_{age}=33.22), and *N*=52 in Experiment 5 (21 females, M_{age}=33.71). As for the other pre-registered exclusion criteria, no participants participated more than once as determined via their Prolific IDs, and no participants provided uniform confidence ratings in Phase Two (i.e. with 80% of ratings below 10% or above 90%) for Experiments 1 through 4.

Apparatus

Participants completed the experiment on their own devices, and were redirected to a website hosted on the JATOS server [56]. Stimulus presentation and data collection were controlled via custom software written in HTML, CSS, JavaScript, and PHP, using the jsPsych library [57]. Their browser window was automatically put in full-screen mode at the beginning of the experiment.

Experiments 1-3

Phase 1: Self. Participants began by completing an image discrimination task illustrated in Figure 1A. On each trial, they were shown two noise images side by side, and one also contained a Gabor patch. The noise images consisted of randomly intermixed white and black pixels, and were randomly selected for each participant on each trial without replacement amongst 1200 possible images. The Gabor patches consisted of sinusoidal gratings tilted at an orientation of 45° or 135° and were superimposed over the white noise with varying transparency, thus varying detection difficulty. Participants indicated which of the two images contained a stimulus via a keypress ('f' for left, 'j' for right), and then rated how confident they were in this choice.

This first phase began with some practice trials, where all gratings were presented at 100% opacity and feedback was given after each trial. Each trial in these practice blocks comprised: (1) a fixation cross (in 42px black Helvetica font), for 500ms; (2) the stimuli (120x120px with a 3px black border each, centred on the screen vertically and at -140 and 140px horizontally), until response; and (3) response feedback ("Correct" or "Wrong") and highlight (in green [#3CB371] if correct, red [#FF0000] if incorrect), for 1000ms. Each block comprised 4 trials (2 grating orientations [45, 135 degrees] × 2 grating positions [left, right stimulus]) in a random order, and was repeated for each participant until their mean accuracy on the last block was at or above 75%.

Next, participants completed an experimental phase, where the grating opacity started at 100%, and was then updated on each block via a staircasing procedure: it decreased if accuracy in the last block was above 75%; increased if accuracy in the last block was below 60%; and remained unchanged otherwise. Decreases and increases occurred in steps of 50, 20, 10, 10, 5, 5, 2, 2, 2, and 1 until convergence – with a maximum and minimum opacity value of 100 and 0, respectively. Each trial comprised: (1) a fixation cross, for 500ms; (2) the stimuli, until response; (3) a blue (#0000FF) response highlight, for 500ms; and (4) a confidence prompt, until response ("How confident are you?", to be answered with a slider from 0 ["I am not confident at all"] to 100 ["I am very confident"]). Each block comprised 8 trials (2 grating orientations [45, 135 degrees] × 2 grating positions [left, right stimulus] × 2 repetitions) in a random order, and was repeated for each participant for a maximum of 200 trials, or until (1) they completed at least 152 trials; and (2) their accuracy in the last 3 blocks was above 60% and below or equal to 75%.

Phase Two: Other. Participants were then introduced to the idea that people can differ quite a lot in how confident they are in their choices, and they were shown sample distributions of confidence ratings from several previous participants for the same choice difficulty. They then began a series of blocks where they were shown choices from other agents and guessed how confident they thought the other agent was in that choice. The other agent was either another participant (Fig. 1B) or an artificial agent (Fig. 1C) – the key manipulation of interest. The artificial agent was referred to either as a 'robot' (Experiments 1 and 2) or as a 'computer algorithm' (Experiment 3).

Each trial in this phase comprised: (1) a fixation cross, for 500ms; (2) the stimuli, until the other agents' response time (see below); (3) a response highlight, for 500ms; and (4) a confidence prompt, until response ("How confident do you think the [other person/robot/computer algorithm] was?", to be answered with a slider from 0 ["The other person/robot/computer algorithm was not confident at all"] to 100 ["The other person/robot/computer algorithm was very confident"]). The opacity of the Gabor stimulus was varied from -5% to 5%, with 0% being the optimal difficulty level determined in Phase 1 – with a maximum and minimum opacity value of 100 and 0, respectively.

Each observer saw two blocks from each agent in a randomised order (i.e., two 'other person' blocks followed by two 'robot/computer algorithm' blocks, or vice versa), and each block comprised 44 trials (2 grating orientations [45, 135 degrees] × 2 grating positions [left, right box] × 11 difficulty levels [from -5 to +5]) in a randomised order. To remind participants of which agent they were observing, we randomly assigned a colour cue (blue [#3C3CA3] or purple [#841F42]) to each agent, separately for each participant. In Experiments 1 and 2, the agent was also depicted in the centre of the screen from the back, as if they were observing the stimuli. Participants were instructed that the image chosen by the other agent would be highlighted at the same time the other person made their choice. Every 11 trials (except for the last trial of each block pair), participants were given feedback about their cumulative performance on this confidence estimation task (as the absolute difference between the estimated confidence and the agents' confidence [see below]).

Both Phase One and the two halves of Phase Two were preceded by comprehension questions regarding which question participants would be asked in the trials to follow (e.g., "After observing the other participant's choice, you will be asked a question. Which one?").

Observed Behaviour. In Experiment 1, the agents' behaviour was determined by matching each observer with one of 20 counterpart participants who had previously completed a similar version of the experiment. In particular, these participants had completed a staircasing procedure (similar to Phase One as described above), followed by four blocks of experimental trials of the Gabor discrimination task, with 44 trials each (2 grating orientations [45, 135 degrees] × 2 grating positions [left, right box] × 11 difficulty levels [from -5 to +5]).

These data were then used to generate the trials for Experiment 1, where on each trial we determined (1) the agent's accuracy, computed from the probability that the counterpart participant would respond correctly at that difficulty level based on a psychometric function fit to their performance; (2) the agent's response time, randomly picked from a gaussian distribution with mean and standard deviation based on the counterpart participant's response times at that difficulty level and accuracy (but only including trials with response time between 200ms and 3000ms, and with these randomly picked values being replaced if they were lower than 200ms); and (3) the agent's confidence, randomly picked from a gaussian distribution with mean and standard deviation based on the counterpart participant's confidence at that difficulty level and accuracy. If the counterpart participant had no trials corresponding to that difficulty level and accuracy, we determined (2) and (3) based on all other trials. Crucially, these generative functions were kept constant for each participant across both agents.

In Experiments 2 and 3, the agents' behaviour was determined not from counterpart participants, but rather from an algorithm. This was a neural network implemented in Tensorflow [58] with three convolutional blocks, each with a max pooling layer, and a fully-connected layer on top. The model was trained to discriminate between Gabor patches and noise stimuli, and an optimal opacity level was selected such that the model would have an average accuracy between 60 and 75% (thus matching the staircasing procedure from Experiment 1). On each trial we determined (1) the agent's accuracy, computed from the probability that the model would correctly classify a stimulus at that subjective difficulty level based on a psychometric function fit to its performance; (2) the agent's response time, randomly picked from a gaussian distribution with a mean of 250ms and a standard deviation of 20ms; and (3) the agent's confidence, randomly picked from a gaussian distribution with mean and standard deviation based on the model's mean accuracy at that difficulty level. Again, these generative functions were importantly kept constant for each participant across both agents.

Debriefing. At the end of the experiment, participants were asked a series of questions regarding their performance (i.e., “How well do you think you did at deciding which box contained the grating?”, and “How well do you think you did at guessing the [other participant/robot/computer algorithm]’s confidence?”), the other agents’ performance (i.e., “How well do you think the [other participant/robot/computer algorithm] did on this task?”), the other agents’ trustworthiness (i.e., “How much would you trust the [other participant/robot/computer algorithm] if you were working together?”), the artificial agent’s functionality (“How do you think the robot/computer algorithm functions? What do you think its capabilities are?”). They were also asked about their demographics (age and gender) and experience in the survey (e.g. technical difficulties or interruptions).

Experiment 4

In this experiment, participants watched other agents pick which of two countries had a larger (or smaller) population and later rated how confident they thought the other agent was in that choice. Each trial thus comprised: (1) a question (“Which of the two countries has a larger/smaller population?”), for 500ms; (2) the question and response options, until the other agents’ response time (see below); (3) a response highlight, for 500ms; and (4) a confidence prompt, until response.

Each participant completed a total of 176 trials divided into two blocks – one for the other person (“another participant who previously completed this task”), and one for the computer algorithm (“a computer algorithm that was built and trained to complete this task”) in a randomised order, with the respective colour cues also randomised. The debriefing questions were the same as in previous experiments, except participants were no longer asked about their own performance in the task.

Observed Behaviour. The trial characteristics and agents’ behaviour were determined by matching each observer with one of 10 counterpart participants who had previously completed the general knowledge task. For this task, we first selected the 53 countries with populations between 25 and 500 million based on the 2021 UN census (https://population.un.org/wpp/). For each counterpart participant, we then randomly selected 176 pairs of countries out of all possible combinations and asked them to select the one with the smaller or larger population – resulting in 176 trials (2 questions [“smaller”, “larger” framing] × 2 country positions [smaller, larger on the left] × 44 country pairs). Each participant in Experiment 4 was then paired with one of these 10 counterpart participants and saw all their 176 trials in a random order, each randomly assigned to either the ‘other person’ or the ‘computer algorithm’ block. The trial characteristics (i.e., prompt and response options) and observed behaviour (i.e., accuracy, response time, and confidence) thus matched the counterpart participants' behaviour exactly – with the only constraint being a maximum response time of 12s.

Experiment 5

In this experiment, participants received advice from other agents in a perceptual decision-making task. Phase One was identical to Experiments 1-3, except participants were no longer asked about their own confidence. Phase Two was instead adapted such that participants first made their own judgments, and later received the advice of another agent, after which they had the opportunity to revise their initial choices. Each trial thus comprised: (1) a fixation cross, for 500ms; (2) the stimuli, until response; (3) a response highlight, for 500ms; and (4) a screen with the advice (e.g., “Your choice: right; Other participant/Computer algorithm's choice: left”) and reversal prompt (“Would you like to change your initial choice? Press 'y' for yes, 'n' for no.”), until response. On some trials (with 10% probability each), this was followed by (5) a catch question (“What was the [other participant/computer algorithm]’s advice on the last trial?”), until response; and (6) feedback on this catch question (“Correct!” or “Wrong!”), for 500ms.

Each participant completed two blocks of 44 trials each (2 grating orientations [45, 135 degrees] × 2 grating positions [left, right box] × 11 difficulty levels [from -5 to +5]) in a randomised order. Each observer completed four blocks – two with advice from another person (“another participant who previously completed this task”), and two with advice from the computer algorithm (“a computer algorithm that was built and trained to complete this task”), with the respective colour cues also randomised. The accuracy of the agents was determined as in Experiment 1, and every 11 trials (except for the last of each block pair), participants received feedback on their accuracy based on their revised choices. The debriefing questions were the same as in previous experiments, except participants were no longer asked about their accuracy in guessing the other agents’ confidence.

Statistical Analysis

All analyses were conducted using R (R Core Team, 2020), RStudio (Rstudio Team, 2020), and packages lme4 [59], lmerTest [60], and emmeans [61].

To examine the impact of observed performance on perceived confidence, we conducted linear mixed-effects models of the effect of task difficulty (target opacity from -5 to +5 [Experiments 1-3] or log ratio of the populations of the two countries [Experiment 4]), accuracy (coded as error: -0.5, correct: 0.5), and response times (Experiments 1 and 4 only) on the confidence estimates, with counterpart participant (out of 20 participants in Experiment 1; out of 10 participants in Experiment 4) and observer number as random intercepts. To examine the relationship between self-directed metacognition and perceived metacognition, we first quantified the effect of trial difficulty on confidence attributions for each observer, agent, and accuracy, by fitting separate linear regression models predicting confidence estimates from difficulty. From these coefficients, we then operationalised other-directed metacognition as the difference between slopes on accurate vs. inaccurate trials, separately for each subject and agent. Self-directed metacognition was operationalised as metacognitive efficiency computed via a hierarchical regression model (the RHmeta-d model, an extended version of the HMeta-d model; see https://github.com/metacoglab/HMeta-d; [62]).

To test whether attributions inferences of confidence might vary depending on whether they concern another person as opposed to an artificial agent, we added to the first model (with difficulty, accuracy, and response times) the agent as a fixed factor (coded as other person: -0.5, robot [Experiments 1-2] or algorithm [Experiments 3-4]: 0.5). To further deconstruct this effect, we ran an exploratory analysis predicting attributions of confidence from accuracy (interacting with difficulty), response time, and agent on the current trial, as well as accuracy (interacting with difficulty), response time, and confidence on each the previous five trials, again with observer number as a random intercept, and discarding the first 5 trials of each block. Next, we checked the consistency of this model across agents by adding agent as an interactive factor to all terms.

To examine learning effects, we conducted linear mixed-effects models of the effect of trial epoch (in 11 intervals of 8 trials each), agent (robot vs. person), and block order (robot first vs. person first) on the confidence estimates, with observer number as a random intercept.

To examine advice-taking behaviour in Experiment 5, we conducted a generalised linear mixed-effects model with the logit link of the effect of task difficulty (target opacity from -5 to +5) and accuracy in the initial choice (coded as error: -0.5, correct: 0.5) on advice-taking behaviour (coded as reject: 0, accept: 1), with counterpart participant (out of 20 participants) and observer number as random intercepts. To test whether advice-taking varied depending on whether the advice was given by another person as opposed to an artificial agent, we added to this model the agent as a fixed factor (coded as other person: -0.5, algorithm: 0.5).

For all models, in the case of convergence or singularity issues, we reduced the complexity of the random effects structure. We followed up on significant effects with post-hoc comparisons using Bonferroni corrections.

References

1. Botvinick, M. M. (2022). Realizing the promise of AI: a new calling for cognitive science. *Trends in Cognitive Sciences.*
2. Cross, E. S., & Ramsey, R. (2021). Mind meets machine: Towards a cognitive science of human–machine interactions. *Trends in Cognitive Sciences, 25*(3), 200-212.
3. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114-126.
4. Dzindolet, M. T., Pierce, L. G., Beck, H. P., & Dawe, L. A. (2002). The perceived utility of human and automated aids in a visual detection task. *Human Factors, 44*(1), 79-94.
5. Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627-660.
6. Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes, 151*, 90-103.
7. Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research*, 56(5), 809-825.
8. Bainbridge, W. A., Hart, J. W., Kim, E. S., & Scassellati, B. (2011). The benefits of interactions with physically present robots over video-displayed agents. *International Journal of Social Robotics, 3*, 41-52.
9. Nussberger, A. M., Luo, L., Celis, L. E., & Crockett, M. J. (2022). Public attitudes value interpretability but prioritize accuracy in Artificial Intelligence. *Nature Communications, 13*(1), 5821.
10. Stanley, J., Gowen, E., & Miall, R. C. (2010). How instructions modify perception: an fMRI study investigating brain areas involved in attributing human agency. *Neuroimage, 52*, 389-400.
11. Cross, E. S., Ramsey, R., Liepelt, R., Prinz, W., & Hamilton, A. F. D. C. (2016). The shaping of social perception by stimulus and knowledge cues to human animacy. *Philosophical Transactions of the Royal Society B: Biological Sciences, 371*, 20150075.
12. Fleming, S. M. (2023). Metacognition and confidence: A review and synthesis. *PsyArXiv.*

13. Bang, D., Aitchison, L., Moran, R., Herce Castanon, S., Rafiee, B., Mahmoodi, A., ... & Summerfield, C. (2017). Confidence matching in group decision-making. *Nature Human Behaviour, 1*, 0117.
14. Pescetelli, N., & Yeung, N. (2021). The role of decision confidence in advice-taking and trust formation. *Journal of Experimental Psychology: General, 150*, 507-526.
15. Gates, V., Callaway, F., Ho, M. K., & Griffiths, T. L. (2021). A rational model of people's inferences about others' preferences based on response times. *Cognition, 217*, 104885.
16. Koriat, A., & Ackerman, R. (2010). Choice latency as a cue for children's subjective confidence in the correctness of their answers. *Developmental Science, 13*, 441-453.
17. Vuillaume, L., Martin, J. R., Sackur, J., & Cleeremans, A. (2020). Comparing self-and hetero-metacognition in the absence of verbal communication. *PloS one, 15*, e0231530.
18. Patel, D., Fleming, S. M., & Kilner, J. M. (2012). Inferring subjective states through the observation of actions. *Proceedings of the Royal Society B: Biological Sciences, 279*, 4853-4860.
19. Goupil, L., & Aucouturier, J. J. (2021). Distinct signatures of subjective confidence and objective accuracy in speech prosody. *Cognition, 212*, 104661.
20. Goupil, L., Ponsot, E., Richardson, D., Reyes, G., & Aucouturier, J. J. (2021). Listeners' perceptions of the certainty and honesty of a speaker are associated with a common prosodic signature. *Nature Communications, 12*, 861.
21. Heyes, C., Bang, D., Shea, N., Frith, C. D., & Fleming, S. M. (2020). Knowing ourselves together: The cultural origins of metacognition. *Trends in Cognitive Sciences, 24*, 349-362.
22. Zarnoth, P., & Sniezek, J. A. (1997). The social influence of confidence in group decision making. *Journal of Experimental Social Psychology, 33*, 345-366.
23. Bahrami, B., Olsen, K., Latham, P. E., Roepstorff, A., Rees, G., & Frith, C. D. (2010). Optimally interacting minds. *Science, 329*, 1081-1085.
24. Daftry, S., Zeng, S., Bagnell, J. A., & Hebert, M. (2016). Introspective perception: Learning to predict failures in vision systems. *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 1743-1750.
25. Gurău, C., Rao, D., Tong, C. H., & Posner, I. (2018). Learn from experience: Probabilistic prediction of perception performance to avoid failure. *The International Journal of Robotics Research, 37*, 981-995.

26. Kadavath, S., Conerly, T., Askell, A., Henighan, T., Drain, D., Perez, E., ... & Kaplan, J. (2022). Language models (mostly) know what they know. *arXiv*, 2207.05221.
27. Lin, S., Hilton, J., & Evans, O. (2022). Teaching models to express their uncertainty in words. *arXiv*, 2205.14334.
28. Fleming, S. M. (2021, April 16). What separates humans from AI? It's doubt. *Financial Times*. https://www.ft.com/content/1ff66eb9-166f-4082-958f-debe84e92e9e
29. Hein, M., Andriushchenko, M., & Bitterwolf, J. (2019). Why relu networks yield high-confidence predictions far away from the training data and how to mitigate the problem. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 41-50.
30. Wittmann, M. K., Kolling, N., Faber, N. S., Scholl, J., Nelissen, N., & Rushworth, M. F. (2016). Self-other mergence in the frontal cortex during cooperation and competition. *Neuron*, *91*, 482-493.
31. Bang, D., Moran, R., Daw, N. D., & Fleming, S. M. (2022). Neurocomputational mechanisms of confidence in self and others. *Nature Communications*, *13*, 4238.
32. Sanders, J. I., Hangya, B., & Kepecs, A. (2016). Signatures of a statistical computation in the human sense of confidence. *Neuron, 90*, 499-506.
33. Fleming, S. M., & Daw, N. D. (2017). Self-evaluation of decision-making: A general Bayesian framework for metacognitive computation. *Psychological Review, 124*, 91-114.
34. Fleming, S. M., Massoni, S., Gajdos, T., & Vergnaud, J. C. (2016). Metacognition about the past and future: quantifying common and distinct influences on prospective and retrospective judgments of self-performance. *Neuroscience of Consciousness, 2016*, niw018.
35. Rahnev, D., Koizumi, A., McCurdy, L. Y., D'Esposito, M., & Lau, H. (2015). Confidence leak in perceptual decision making. *Psychological Science, 26*, 1664-1680.
36. Pleskac, T. J., & Busemeyer, J. R. (2010). Two-stage dynamic signal detection: a theory of choice, decision time, and confidence. *Psychological Review, 117*, 864-901.
37. Chong, L., Zhang, G., Goucher-Lambert, K., Kotovsky, K., & Cagan, J. (2022). Human confidence in artificial intelligence and in themselves: The evolution and impact of confidence on adoption of AI advice. *Computers in Human Behavior, 127*, 107018.

38. Costen, C., Rigter, M., Lacerda, B., & Hawes, N. (2022). Shared autonomy systems with stochastic operator models. In *International Joint Conferences on Artificial Intelligence Organization*, 1-11.
39. Azaria, A., Azoulay, R., & Reches, S. (2023). ChatGPT is a remarkable tool--for experts. arXiv, 2306.03102.
40. Kiani, R., Corthell, L., & Shadlen, M. N. (2014). Choice certainty is informed by both evidence and decision time. *Neuron, 84*(6), 1329-1342.
41. Kruger, J., Wirtz, D., Van Boven, L., & Altermatt, T. W. (2004). The effort heuristic. *Journal of Experimental Social Psychology, 40*, 91-98.
42. Konovalov, A., & Krajbich, I. (2017). On the strategic use of response times. *SSRN Electronic Journal.*
43. Wang, D., & Ziano, I. (2022). Faster responders are perceived as more extraverted. *Journal of Experimental Psychology: General, 151*, 3177-3197.
44. Critcher, C. R., Inbar, Y., & Pizarro, D. A. (2013). How quick decisions illuminate moral character. *Social Psychological and Personality Science, 4*, 308-315.
45. Graziano, M. S. (2019). Attributing awareness to others: the attention schema theory and its relationship to behavioural prediction. *Journal of Consciousness Studies, 26*, 17-37.
46. Elekes, F., & Király, I. (2021). Attention in naïve psychology. *Cognition, 206*, 104480.
47. Colombatto, C., & Scholl, B. J. (2022). Unconscious pupillometry: An effect of "attentional contagion" in the absence of visual awareness. *Journal of Experimental Psychology: General, 151*, 302-308.
48. Fleming, S. M., Weil, R. S., Nagy, Z., Dolan, R. J., & Rees, G. (2010). Relating introspective accuracy to individual differences in brain structure. *Science, 329*, 1541-1543.
49. Rouault, M., Seow, T., Gillan, C. M., & Fleming, S. M. (2018). Psychiatric symptom dimensions are associated with dissociable shifts in metacognition but not task performance. *Biological Psychiatry, 84*, 443-451.
50. Rollwage, M., Dolan, R. J., & Fleming, S. M. (2018). Metacognitive failure as a feature of those holding radical beliefs. *Current Biology, 28*, 4014-4021.

51. Schulz, L., Rollwage, M., Dolan, R. J., & Fleming, S. M. (2020). Dogmatism manifests in lowered information search under uncertainty. *Proceedings of the National Academy of Sciences, 117*, 31527-31534.
52. Frith, C. D. (2012). The role of metacognition in human social interactions. *Philosophical Transactions of the Royal Society B: Biological Sciences, 367*, 2213-2223.
53. Grosse Wiesmann, C., & Southgate, V. (2021). Early theory of mind development: Are infants inherently altercentric?. In *The neural basis of mentalizing* (pp. 49-66). Cham: Springer International Publishing.
54. Manea, V., Kampis, D., Grosse Wiesmann, C., Revencu, B., & Southgate, V. (2023). An initial but receding altercentric bias in preverbal infants' memory. *Proceedings of the Royal Society B: Biological Sciences*, *290*, 20230738.
55. Palan, S., & Schitter, C. (2018). Prolific. ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance, 17*, 22-27.
56. Lange, K., Kühn, S., & Filevich, E. (2015). "Just another tool for online studies"(JATOS): An easy solution for setup and management of web servers supporting online studies. *PloS one, 10*, e0130834.
57. De Leeuw, J. R. (2015). jsPsych: A JavaScript library for creating behavioral experiments in a Web browser. *Behavior Research Methods, 47*, 1-12.
58. Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., ... & Zheng, X. (2016). Tensorflow: Large-scale machine learning on heterogeneous distributed systems. *arXiv* preprint arXiv:1603.04467.
59. Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software, 67*(1), 1-48.
60. Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). "lmerTest Package: Tests in Linear Mixed Effects Models." *Journal of Statistical Software*, *82*(13), 1-26.
61. Lenth R (2022). *emmeans: Estimated Marginal Means, aka Least-Squares Means*. R package version 1.8.2, <https://CRAN.R-project.org/package=emmeans>.
62. Harrison, O. K., Garfinkel, S. N., Marlow, L., Finnegan, S. L., Marino, S., Köchli, L., ... & Fleming, S. M. (2021). The Filter Detection Task for measurement of breathing-related interoception and metacognition. *Biological Psychology, 165*, 108185.

Acknowledgments

The authors thank Tali Sharot, Moshe Glickman, and members of the UCL MetaLab for helpful comments and discussions. This work was supported by a UKRI/EPSRC Programme Grant [EP/V000748/1]. SMF is a CIFAR Fellow in the Brain, Mind and Consciousness Program, and is funded by a Sir Henry Dale Fellowship jointly funded by the Wellcome Trust and the Royal Society (206648/Z/17/Z) and a Philip Leverhulme Prize from the Leverhulme Trust.

Author Contributions

All authors designed research and wrote the manuscript; C.C. conducted the experiments, and analysed data with input from S.M.F.

Competing Interests

The authors declare no competing interests.

Open Practices

Anonymised raw data and analysis code for all experiments are openly available on the Open Science Framework (OSF) website at this link: https://osf.io/8tphs/?view_only=3d3b5cecb629486a9ace79f9be6d558d. All experiments were pre-registered (Exp. 1: https://osf.io/um5h2/?view_only=b584d55467d84b9e981d480ca42402d8; Exp. 2: https://osf.io/s8ebv/?view_only=9e03b49b06924a139737b66a07ae9e7a; Exp. 3: https://osf.io/vue42/?view_only=05ac2c7ea9c94c4c87d492f8ebdd53a0; Exp. 4: https://osf.io/y3zu8/?view_only=99fefed2b42c4bdeaf0386a8d136b736; Exp. 5: https://osf.io/8ca53/?view_only=c4310ba3e97640e9a565100c0de62efb).