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Cognitive Challenges in Human–Artificial Intelligence Collaboration: Investigating the Path Toward Productive Delegation

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Abstract. We study how humans make decisions when they collaborate with an artificial intelligence (AI) in a setting where humans and the AI perform classification tasks. Our experimental results suggest that humans and AI who work together can outperform the AI that outperforms humans when it works on its own. However, the combined performance improves only when the AI delegates work to humans but not when humans delegate work to the AI. The AI's delegation performance improved even when it delegated to low-performing subjects; by contrast, humans did not delegate well and did not benefit from delegation to the AI. This bad delegation performance cannot be explained with some kind of algorithm aversion. On the contrary, subjects acted rationally in an internally consistent manner by trying to follow a proven delegation strategy and appeared to appreciate the AI support. However, human performance suffered as a result of a lack of metaknowledge—that is, humans were not able to assess their own capabilities correctly, which in turn led to poor delegation decisions. Lacking metaknowledge, in contrast to reluctance to use AI, is an unconscious trait. It fundamentally limits how well human decision makers can collaborate with AI and other algorithms. The results have implications for the future of work, the design of human–AI collaborative environments, and education in the digital age.

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Keywords: future of work • artificial intelligence • machine learning • delegation • metaknowledge • human–AI collaboration

1. Introduction

Early artificial intelligence (AI) that tried to mimic human decision rules was only partly successful, as it suffered from what Autor (2014) calls Polanyi's paradox: the fact that humans can often not accurately describe the decision rules they use to solve a problem. Modern AI approaches such as deep neural networks seem to overcome this limitation by learning flexible models from large training sets instead of relying on human-described rules (LeCun et al. 2015, Schmidhuber 2015). AI is now widely applicable and effective, and it is perceived as a general-purpose technology (McAfee and Brynjolfsson 2017) that fuels innovation in diverse domains, such as medicine (Kononenko 2001, Esteva et al. 2017), and generic perceptional tasks, such as processing images, text, and speech (Hinton et al. 2012, Deng and Yu 2013). We agree that AI performance will likely improve further and that AI will be embedded in our day-to-day life. But, as Brynjolfsson et al. (2018) point out, not all decision making can be automated completely, as some tasks remain challenging for AI.

Perhaps the best prediction we can make today is that humans will remain integral to the workplace, and they will work together with AI, algorithms, or intelligent machines. This is reflected in current information systems (IS) research, as evidenced by special issues on augmented intelligence in *Information Systems Research* and on managing AI in *MIS Quarterly*, both published in 2021. Baird and Maruping (2021) propose a theoretical framework for the next generation of IS research focusing on delegation from and to information systems, such as AI. They explicitly state that both the information system and the human could be the delegating unit. This mindset is in line with the concept of human-in-the-loop AI (Zanzotto 2019), where humans remain an integral part of AI decision making.

The critical question in delegation is how firms should distribute work between humans and AI. Polanyi's work points to a facet of human decision making that is critical to the discussion but vastly ignored until now. When humans can solve a problem but are unable to explain their decision rules clearly, they should, nonetheless, be able to contribute complementarities to an algorithm (Autor et al. 2003). Because humans have different experiences and education, decision models and knowledge also differ between individual humans, as well as between humans and AI. Because we cannot articulate our idiosyncratic "decision rules" well, it is hard for learning algorithms to imitate them precisely, even from large training sets. Humans' inability to tell what they know shields their abilities from perfect digital imitation. The variety of human thought, only partially observable through their actions, creates the possibility that humans have complementary knowledge with respect to AI algorithms. The AI, on the other hand, may find a way to solve a problem no human being has thought about before. Thus, both humans and the AI potentially have complementary knowledge, and the performance of humans working with an AI system may be better than that of the AI system (or humans) working alone.

Our study focuses on the case where either an AI algorithm or a human is allowed to perform a task unaided or to delegate that task to the other actor. On a generic level, there are three main boundary conditions that enable the combined performance to exceed the performance of the better-performing actor:

1. *Existence of complementarities:* In order to enhance performance through delegation between two actors, complementary knowledge has to exist between the two actors—that is, a human and an AI system. We claim that this should be the case for all tasks where Polanyi's paradox applies (i.e., where humans cannot exactly specify their decision rules).

2. *Recognition of complementarities:* A delegating partner needs to recognize that complementarities between the two partners exist and that the tasks should be performed by the better-suited partner. Although having information on the other partner's ability helps, the most important ability is to be able to estimate one's own ability. If one actor—say, an AI system—knows that it can perform a task, it is always wise for that actor to complete the task itself. On the other hand, it is wise to delegate if the actor knows that it cannot perform the task but its partner—in this case, a human—potentially can. In line with Lories et al. (1998) and Evans and Foster (2011), we denote this ability to assess one's own capabilities as *metaknowledge*. Therefore, we argue that metaknowledge is a crucial resource for recognizing complementarities.

3. *Execution of efficient delegation rules:* Once a delegating partner recognizes complementarities, that actor should delegate tasks to the better-suited actor. Although this can be easily constructed and executed for an AI system, humans have to be willing to construct and follow such a delegation rule.

In a series of behavioral experiments, we investigate how work is delegated between humans and an AI algorithm. When designing the experiments, we aimed at making the results as generalizable as possible. Central to the paper is a delegation rule that does not make assumptions about the context in which it is used. Furthermore, we conducted the experiments in a context where humans make good decisions naturally, and modern AI performs equally well or even better. We chose an environment where humans do not require any specific training. Contexts requiring specific training make the results less generalizable, whereas abilities in more general settings can carry over into more specialized tasks. Furthermore, expertise may not enable better decision making: metaknowledge seems to be only minimally increased by training (Hansson et al. 2008), and trained experts could even show lower levels of metaknowledge compared with inexperienced subjects (Brezis et al. 2018).

Therefore, we chose image classification as the focal task for our experiments. Although humans are naturally skilled at it, deep learning has improved AI algorithms beyond the human performance level recently (Russakovsky et al. 2015). In our experiments, humans and an AI algorithm work together on the same image classification tasks. In the rest of the paper, we refer to the image classification AI algorithm simply as the "AI." Humans can delegate images to the AI, and the AI can delegate images to humans in a condition called inversion.

Such collaboration between AI systems and humans is currently underresearched. A related field analyzes human decision makers' attitude toward algorithms. Several researchers have documented the reluctance of human decision makers to use algorithms (Dawes 1979, Bazerman 1985, Kleinmuntz 1990), although some recent research has challenged this notion. In a more recent seminal work, Dietvorst et al. (2015) demonstrated that humans might react more strongly to errors made by machines than to errors made by humans, even if the machine performs better and if its errors are smaller than those of human decision makers. The authors label this loss of confidence "algorithm aversion," a term picked up willingly by the popular press. But neither Dietvorst et al. (2015) nor a follow-up study (Dietvorst et al. 2018) document general human distrust toward algorithms. Logg et al. (2019) study multiple prediction tasks and find that humans are indeed willing to work with machines, a tendency they label as "algorithm appreciation."

We are not aware of research that studies delegation between AI and humans in a setting with complementary skills or explores fundamental factors that might hinder or support collaboration. The central questions that our study answers are as follows:

- *Study* 1: Can delegation between humans and AI outperform humans or AI working alone, and who can delegate better?
- *Study* 2: What factors limit human delegation performance? How can we overcome these limitations?

Our experiments reveal that whereas the AI improves considerably by delegating to humans, humans are naturally bad delegators to the AI. Even worse—and more interesting—humans' performance only slightly improves when they are taught a good delegation rule, even when they apply it consistently and rationally. We observe little or no bias against the use of AI; in other words, our results indicate that our subjects do not exhibit general algorithm aversion. Instead, humans try to work with the AI to the best of their abilities but fail despite their best intentions. Humans seem to be unable to judge their own capabilities and the difficulty of the task, which in turn leads to bad delegation decisions. Thus, humans delegating to the AI do not meet the boundary condition of a sufficient level of metaknowledge to enable a successful human–AI collaboration. We also conduct additional robustness studies addressing the impact of continuous feedback and increasing task difficulty.

In the following, we summarize the theoretical underpinnings of our study and differentiate our study from the existing literature. We discuss theoretical antecedents in Section 2, describe the experimental studies and the robustness checks in Sections 3 and 4, and conclude with a discussion and an outlook on future research directions in Section 5.

2. Theory

We describe extant work and theories that inform our research questions and experimental design. In the following subsections, we discuss contributions of our work. Specifically, we shed light on human attitude toward algorithms (Section 2.1) and consider the role of delegation settings (Section 2.2), complementarities on the task instances level (Section 2.3), and feedback (Section 2.4) to lay the foundation for our work.

2.1. Attitude Toward AI

Research that studies how humans use computers for problem solving dates back decades and includes works that compare human decisions with results from mathematical models (Meehl 1954). Even during the infancy of computing environments in the 1950s, some computer models outperformed human decision makers. It was observed that in many instances, humans were reluctant to use algorithms, despite possible performance benefits (Dawes 1979, Bazerman 1985, Kleinmuntz 1990). However, other studies, such as Dijkstra (1999), demonstrated general willingness of humans to use algorithms, even allowing machines to overrule their own inferior decisions. How humans make decisions in concert with algorithms has been revisited lately and has been of great interest with the surge in usage of AI techniques. Current applications look at investor usage of roboadvising services in fintech (Ge et al. 2021), reactions to AI advice in healthcare (Jussupow et al. 2021), and the effect of similarity to human language used by chatbots (Schanke et al. 2021).

In a seminal work on attitude toward algorithms, Dietvorst et al. (2015) demonstrate that humans react differently to errors made by humans compared with algorithms. In their experiments, they let humans work with AI algorithms for prediction tasks. When the subjects saw the AI perform—and err, they lost confidence in it. Interestingly, this loss is much stronger than the loss in confidence in humans who made mistakes in the same task. The authors label this tendency "algorithm aversion." Logg et al. (2019) studied whether human decision makers prefer advice from other humans or algorithms and found that decision makers show a clear tendency for preference for algorithmic advice over human advice. This preference holds for multiple prediction tasks, and (according to a survey the authors conducted) was not expected by most academics. In contrast to Dietvorst's work, Logg et al. (2019) label their results as "algorithm appreciation." Although this seems like a contradiction, Dietvorst's work does not show a general aversion toward algorithms but rather a different reaction toward errors made by algorithms and human decision makers.

2.2. Delegation

We consider a scenario where a human has to perform a task without information about the solution or performance of the AI for a specific task. We denote this as a "delegation" scenario. We allow delegation to work in both directions. The human may delegate work to the machine, and the machine may delegate work to the human. The latter approach is sometimes called inversion, or using the human as an exit option (McAfee 2013). In delegation settings, a good decision heuristic is the following: "If I am certain to know the correct answer, I should do the job. If I am uncertain, I should delegate!" This rule works well because delegating a task that the decision maker is not able to perform cannot decrease performance, independent of the other party's abilities.

When humans apply this rule, they have to rely on their metaknowledge. This is the ability to assess one's own capabilities—that is, to "know what you know" (Lories et al. 1998, Evans and Foster 2011). A decision maker with strong metaknowledge can delegate well, as she will know whether her answer is correct or not. If her level of metaknowledge is insufficient, she might be certain that incorrect answers are correct, and she might be uncertain about correct answers. In such cases, the joint performance of a human and an algorithm will suffer as a result of inappropriate delegations.

Note that this entire idea—to delegate tasks when one is uncertain—is particularly relevant if delegation does not move an entire stack of tasks, or all the work, but when it occurs on the level of task instances. We discuss this in the next section.

2.3. Complementarity on the Instance Level

Occupations typically consist of bundles of tasks (Autor et al. 2003); some of these tasks are suitable for machine learning, others are not (Brynjolfsson and Mitchell 2017). Because of this, many experts do not expect that AI will automate entire bundles of tasks associated with a job but only specific parts of the bundle (Brynjolfsson et al. 2018). Therefore, a likely consequence of automation on the task level is that some tasks are automated whereas others are not. This leads to redesigned job profiles and workflows based on the economic benefits associated with such work arrangements. For example, Agrawal et al. (2018) discuss ways to compute the economic value of automation on the task level and present a related AI canvas.

We take this argument further and argue that structural complementarities between humans and AI may exist even on the *task instance* level. Our reasoning builds on the design principles for current AI systems. Although traditional expert systems were built by humans who coded concrete decision rules, current AI algorithms discover their own decision rules based on training data. Because of structurally different decision rules, we argue that for each task there might be instances where human decision rules work better than AI decision rules, and vice versa.

Sharing work between humans and AI algorithms on the task level can leverage these complementarities, and joint performance of an AI working with humans may exceed the performance of either of the parties individually. Even if the AI performance is better than the human performance, the optimal allocation will assign some work to a human and some to the AI, and humans and AI both can provide value. Therefore, it is important to conduct research in the area of human–AI collaboration on the level of task instances. As we demonstrate in this paper, it offers significantly different implications for the future of work than the established paradigms have argued.

2.4. The Role of Feedback

Whereas some extant research has used the effect of feedback on task-level performance and accuracy, we decided to not include such feedback in our main experiments, to concentrate on our research questions. The reason for our decision is manifold. For successful human–AI collaboration, several factors have to be considered on the human side of the equation. When previous researchers considered environments where humans make their decisions on the basis of observed AI performance and errors, they found that receiving immediate feedback on AI performance might trigger behavioral effects that undermine the collaborative setting. Examples include diminished trust in algorithms (lower adherence to algorithmic advice) when humans see the algorithm err (Dietvorst et al. 2015) or the overweighting of signals from forecasting errors (Kremer et al. 2011). In the latter case, errors resulting from random variation of data are misinterpreted as systematic errors.

There are many situations where AI feedback is not available or practical—for example, when predicting long-term effects such as climate change (Logg et al. 2019). In other situations, decisions have to be made quickly, such as in autonomous driving or, very frequently, such as in digital markets. In these contexts, either AI errors are not available, it may not be economical to consider them repeatedly, or there may simply be no time to integrate AI performance in decision making.

Although we do not study the effects of feedback in our main study, we do explore whether continuous feedback affects our findings in a dedicated study in the robustness check section. In the following sections, we provide details of our experimental studies.

3. Experimental Studies

After providing a rationale on the study context, we describe the hypotheses, designs, and results of two primary experimental studies with 902 subjects in total. We followed Nosek et al. (2018) and preregistered the experiments at the Open Science Foundation (Foster and Deardorff 2017), including the recruitment and data collection process, the initial hypotheses, and the statistical analysis.

3.1. Study Context

When designing the experimental studies, we aimed for a nonspecialized setting, as we claim that contexts that do require specific training make results less generalizable, whereas findings in general tasks can carry over to more specialized tasks. We also aimed for a task where the three boundary conditions for value-adding delegation between humans and AI are potentially met: (1) the existence of complementarities,

(2) the recognition of complementarities, and (3) the execution of efficient delegation rules. We chose image classification as our experimental study context. Image classification is the task of assigning a focal image to a class. A class can be thought of as a content group. A classification is correct if the focal image is assigned to the right class (a focal picture with the ground truth "poodle" is assigned to the "poodle" class, not to "husky" or "cat"). The research design follows the logic of Fügener et al. (2021): We sampled 100 focal images with known class labels from the ImageNet database. The ImageNet database consists of tens of millions of human-annotated images that are used by current image recognition challenges, such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al. 2015). We sample images used in the ILSVRC image classification task that contain everyday objects and animals and that are assigned to one of 1,000 possible classes. The difficulty of each task may be associated with three main dimensions:

1. *The image itself:* This might include the visibility of the object, size of the object, or whether multiple objects are present.

2. *Possible classes:* A main driver for the difficulty of image classification tasks is the definition of possible choices. For example, fine-grained recognition between similar classes, such as breeds of dogs, is more difficult to achieve than it is with more dissimilar classes, such as between a zebra, lion, or tiger.

3. *The annotator:* Familiarity with the image and with possible classes is a big driver of subjective difficulty. This could depend on training data (in the case of an AI) or on personal experiences and interests (in the case of a human).

A difficulty of human annotators is to cope with a large number of classes, as they might not be aware of the existence of a specific class (Russakovsky et al. 2015). To avoid this effect, we chose to display 10 possible classes along with the focal image. As in Russakovsky et al. (2015), we illustrated each possible answer class by name and 13 example images. One answer was correct. A central performance measure was classification accuracy, the percentage of correctly classified images.

We chose GoogLeNet Inception v3 (Szegedy et al. 2016) as our AI. It is among the best AIs for image classification and was trained on the ImageNet database with 1,000 classes. GoogLeNet assigns a score to each class that can be interpreted as the likelihood of being correct. We obtained its classification accuracy by applying it to the 100 images and by comparing the image with the highest score to the correct answer. As the AI is trained based on outcome data, the decision rules differ from human decision rules, and complementarities between the AI and humans should exist.

We recruited human subjects via Amazon's Mechanical Turk (MTurk). We believe that using MTurk to recruit subjects is particularly suitable for our study for the following reason: we are interested in assessing basic human capabilities, and image classification is a natural task for humans that requires no specific training. Many tasks at MTurk relate to classification problems (Difallah et al. 2015); thus, our experiment is a natural task for MTurk workers. We provide evidence that subjects took the tasks seriously and performed them with a high degree of internal validity. They made logical delegation decisions based on their internal assessment (see Figure 6 and the subsequent discussion).

Study 1, which we call "Delegation and Inversion," compares four different types of delegation: AI working alone, humans working alone, humans who may delegate to AI, and an AI that may delegate to humans (inversion). As expected, the AI outperforms humans. Surprisingly, the AI delegates better than humans when it follows a simple rule. Study 2, titled "Explaining and Enforcing a Delegation Strategy," explores the root cause for poor human delegation and analyzes the effects of teaching humans a similar strategy to that of the AI.

3.2. Study 1: Delegation and Inversion

3.2.1. Hypotheses. Study 1 tackles our first research question: Can delegation outperform humans or AI working alone, and who can delegate better? Thus, we compare four different settings: AI working alone, humans working alone, humans who may delegate to AI, and an AI that may delegate to humans (inversion). We chose image classification as focal task and use an AI that is expected to perform (slightly) above human performance. Our key measure is classification accuracy. We formulated and preregistered four initial hypotheses considering the relation of accuracy between those options. In the following, we present three of those hypotheses and theory that motivates them. One preregistered hypothesis claimed that a state-of-the-art AI outperforms human decision makers, on average. Although this is supported for our specific setting (Szegedy et al. 2015, 2016), it lacks generality, and we decided to exclude it.

The first two hypotheses motivate the value added through delegation. In the introduction, we defined three boundary conditions: the existence of complementarities between the AI and humans, the recognition of complementarities, and the execution of efficient delegation rules. We assume the first property, the existence of complementary knowledge, to hold for all tasks that follow Polanyi's paradox, such as image classification. Although we are not aware of any structural evidence regarding the recognition of complementarities and the execution of efficient delegation rules, there is ample research from the domain of humans working with decision support systems, ranging from seminal theoretical work, such as that of Huber (1990), to recent experimental studies as carried out in Dietvorst et al. (2018), confirming that humans can benefit from working with advanced information technologies and that the second and third boundary conditions are at least partially given. This directly leads to our first hypothesis.

Hypothesis 1.1. *Humans who can delegate tasks to the AI (after seeing the image to be classified) perform better than humans who cannot.*

A more difficult question is to hypothesize on the effect of providing AI the possibility to delegate to humans (inversion), given that human performance is potentially inferior to that of the AI. To be able to improve accuracy, the AI has to delegate those tasks that AI is not able to execute but humans potentially are. For the second boundary condition, the recognition of complementarities, it is important that the AI can assess its own certainty—that is, probability of success. Assessing its own certainty is a main feature of modern AI that has gone through appropriate level of training and enables the AI to perform in a robust manner by using its certainty assessment to make the final choice. In our case of image classification, the AI score of the sample of 100 images estimated an average likelihood of being correct of 0.769 and classified 77 images correctly. Using the AI score as an indicator for certainty and some benchmark for expected human certainty, we define an efficient delegation mechanism that the AI follows to leverage the potential of complementary knowledge. We formulate our next hypothesis.

Hypothesis 1.2. *An AI that can delegate image classification tasks to humans (after seeing the image) performs better than an AI that cannot.*

In theory, both delegation and inversion could achieve the same accuracy: if the delegating actor—say, a human—delegates all tasks that she or he is not able to perform, all tasks that at least one could perform would be considered correct. We denote this as ex post optimal combination of humans and AI, where all complementarities are realized. The AI in our inversion condition applies such a strategy under uncertainty.

Whether humans or AI are better at delegating tasks might depend on the second and third boundary conditions of successful delegation: humans need to have a sufficient level of metaknowledge—that is, correctly identifying tasks where they do not perform well, and humans have to come up with an efficient delegation strategy and be willing to follow it through. We know that the AI has a very high level of metaknowledge and will follow an efficient delegation strategy, whereas both boundary conditions are uncertain for human delegators. This leads to our final hypothesis of Study 1.

Hypothesis 1.3. *AI that can delegate image classification tasks to humans performs better than humans who can delegate to the AI.*

In the following, we lay out the details of our study design before presenting our results.

3.2.2. Design.

We compare classification accuracy between four conditions. In the "AI alone" condition (condition 1), GoogLeNet classified alone. In the "humans alone" condition (condition 2), subjects classified alone. Subjects in the delegation condition (condition 3) could choose for each image to either classify alone or to delegate the image to the AI (subjects were informed about the AI accuracy measure). In the inversion condition (condition 4), the AI could choose for each image to classify alone or to delegate the image to humans.

For conditions 2–4, we ran a between-subjects design with 449 subjects in August 2018. We randomly assigned subjects to the conditions humans alone (149 subjects), delegation (154 subjects), and inversion (146 subjects). The humans alone and inversion conditions (conditions 2 and 4) were identical. Figure 1 shows a screenshot of the humans alone/inversion and delegation conditions.

In the delegation conditions, we added a button labeled "Delegate this question to the AI" at a random position between the answers. If a subject clicked, she did not classify the image herself but delegated it to the AI. She would not see the AI's answer. The AI's answer was considered hers, and she received her payment accordingly. We made it clear that each correct classification earned a payment, regardless of whether the AI or the human classified the image. Subjects in the delegation condition were informed about the AI and its accuracy at the beginning of the experiment.

To ensure that the effects can be related to different delegation, and not to different human classification behavior, subjects in the inversion condition had to classify all 100 images, similar to subjects in the other conditions. We constructed the results for the inversion condition (condition 4) after the experiment. The AI classifies images or delegates them to humans based on a simple rule: if the certainty score for the best answer was below a certain threshold, then GoogLeNet delegated this image to the humans. Otherwise, GoogLeNet classified the image. To simulate this mechanism we paired GoogLeNet with each subject from the inversion condition. The threshold was the average accuracy of subjects in the humans alone condition (condition 2). The AI thus delegated all

Figure 1. (Color online) Screenshots of the Humans Alone/Inversion Condition (Left) and the Delegation Condition (Right)

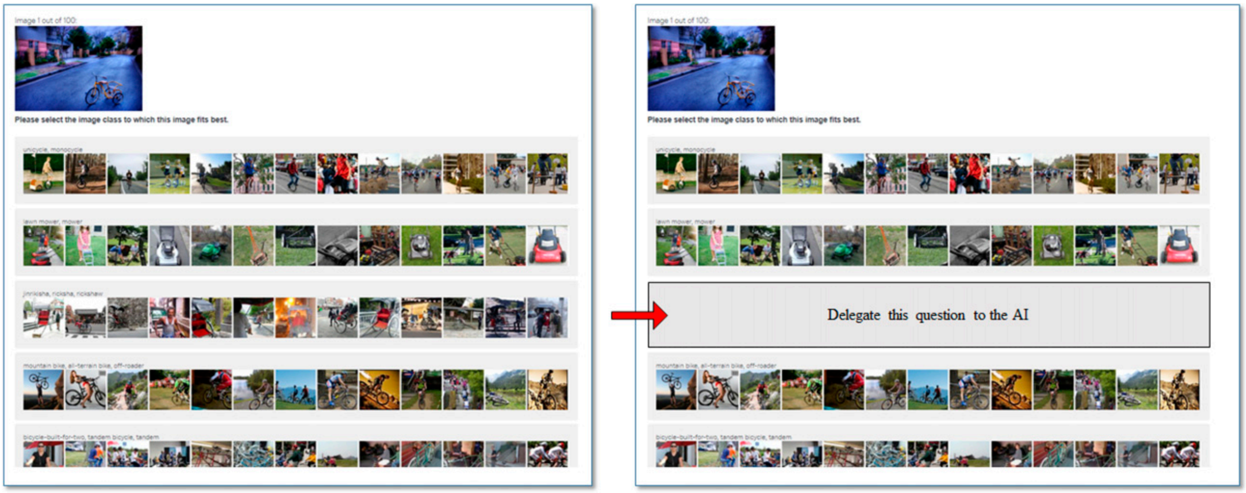


Image 1 out of 100:

Please select the image class to which this image fits best.

unicycle, monocycle
lawn mower, mower
jinrikisha, ricksha, rickshaw
mountain bike, all-terrain bike, off-roader
bicycle-built-for-two, tandem bicycle, tandem
Image 1 out of 100:
Please select the image class to which this image fits best.
unicycle, monocycle
lawn mower, mower
Delegate this question to the AI
mountain bike, all-terrain bike, off-roader
bicycle-built-for-two, tandem bicycle, tandem

images where the estimated likelihood of being correct was below average human accuracy.

All subjects received instructions, had to pass a short quiz so that we could exclude bots, and completed an example classification to ensure that they understood the task. They then had to classify the 100 images in random order. Each subject received a base fee of 50 cents and an additional 5 cents for each correct answer. Afterward, they were asked how many images they think they classified correctly. They could earn an additional dollar if this estimation did not differ from the actual number by more than five images.

The average pay was $4.45, slightly above average pay on MTurk in general (Hara et al. 2018). The average duration of the experiment was 57.7 minutes.

3.2.3. Results. Descriptive statistics (see Table 1) and visual evidence (see Figure 2) suggest that the ability to delegate affects classification accuracy. On average, accuracy is highest in the inversion condition (87.0%), followed by the delegation condition (74.0%) and humans alone (71.7%). By itself, AI accuracy is 77.0% (vertical dashed line in Figure 2). The standard deviation of accuracy (in number of images) is highest when humans work alone (13.2), smaller when humans can delegate (10.1), and smallest when the AI delegates to humans (4.2). We used 0.717 as the threshold in the inversion condition. The results for inversion are robust for different threshold values (inversion accuracy is above 0.840 for all thresholds between the 25th and 75th percentiles of human performance—that is, 0.650 and 0.810). The ex post optimal combination of humans and AI of condition 1 would lead to an upper bound of 89.9% average accuracy—that is, assuming that each image is classified correctly, where either the AI or the (randomly picked) human classified the image correctly.

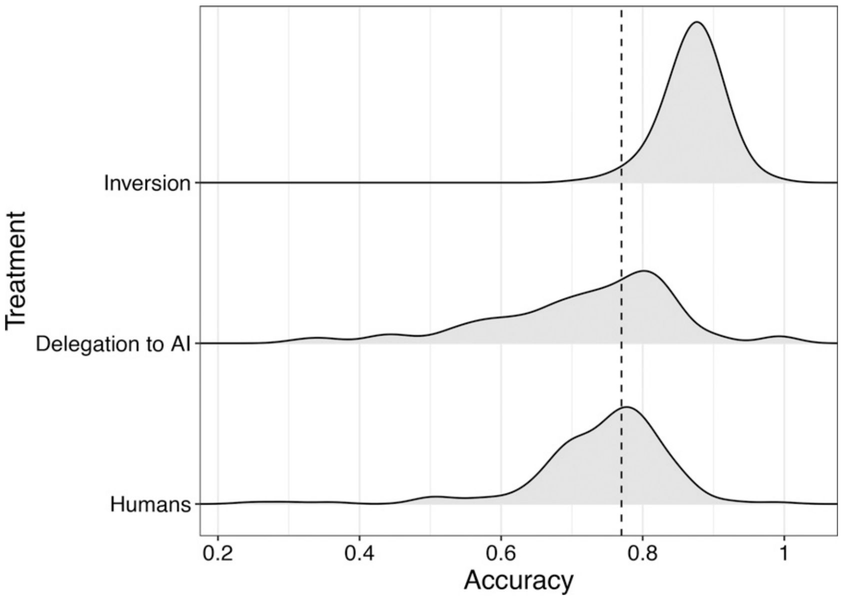
The variance of accuracy is significantly different across experimental conditions (Levene's test: $F(2, 446) = 36.752$, $p < 0.001$; Hartley's F_{max} test: $F_{max} = 9.962 >$ critical value), and means are significantly different as well (analysis of variance (ANOVA) with heterogeneous variances: $F(2, 245.05) = 178.41$, $p < 0.001$, $\eta^2 = 0.315$, which represents a large effect). Post hoc tests with Tamhane's T2 statistic for multiple comparisons show that most pairwise mean differences are significant (see Table 2 for a summary of pairwise comparisons). Humans in the delegation condition seem to outperform humans alone. However, this difference (2.37 percentage points) is not significant ($p = 0.120$) and represents a relatively small effect ($d = 0.2$). Inversion clearly outperforms humans alone. This difference (15.38 percentage points) is significant ($p < 0.001$) and represents a large effect ($d = 1.67$). Inversion also outperforms

Table 1. Study 1 Summary Statistics for Accuracy (Dependent Variable: *Accuracy*)

Condition	*N*	Min	Mean	Max	SD	25th pctl	Median	75th pctl
AI alone			0.770					
Humans alone	149	0.310	0.717	1.000	0.132	0.650	0.740	0.810
Delegation	154	0.250	0.740	0.990	0.101	0.700	0.760	0.800
Inversion	146	0.710	0.870	0.980	0.042	0.850	0.870	0.898

Note. pctl, percentile.

Figure 2. Study 1 Distribution Plots for Accuracy per Experimental Condition



Note. The vertical dashed line is the AI classification accuracy of 77%.

the delegation condition. This difference (13 percentage points) is significant ($p < 0.001$) and represents a large effect ($d = 1.56$).

Mean accuracies for the humans alone, delegation, and inversion conditions are significantly different from AI alone ($p < 0.001$), and except for inversion, are all lower than AI alone. Performance in the inversion condition is significantly higher than when the AI is working alone, suggesting that humans can improve the performance of an AI by providing their input. Not only is inversion better than the other settings on average, we also notice that the AI benefits from working with almost all humans. In the inversion condition, only three of the 146 AI-human pairs had a performance smaller than the AI itself; even the 25th accuracy percentile of inversion (85.0%) is much larger than AI accuracy. To summarize, sharing work between humans and AI could outperform humans and AI working alone. Inversion was highly effective, but human delegation was not.

To understand inferior human performance in the delegation condition, we investigate how humans delegate. In Figures 3 and 4, image difficulty is depicted on the horizontal axis. Image difficulty is the average accuracy in the humans alone condition of the respective image. A 0.2 difficulty/accuracy means 20% of subjects classified the image correctly. The vertical axis in both figures shows the delegation rate (i.e., the ratio of subjects who delegated the image to the AI).

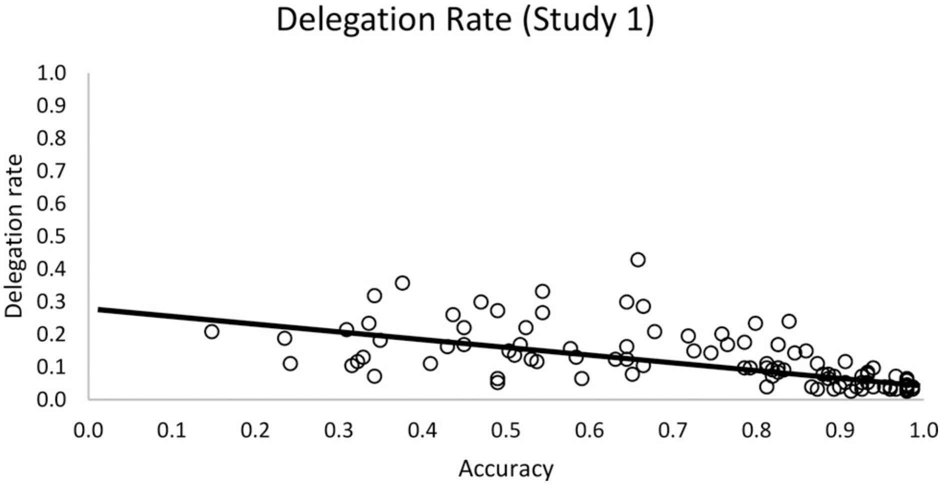
If we consider the entire data set (Figure 3), a weak trend can be detected where images with higher accuracy (lower difficulty) are delegated less often, and vice versa. Thus, humans seem to "rationally" delegate those images more often, which they are less able to classify correctly. However, if we partition the data into images with less than 70% accuracy (these images are more difficult than average human performance) and above 70% accuracy (these images are easier than average human performance), the pattern changes (Figure 4): human delegation is not influenced by the difficulty of an image if the image is relatively "difficult." Human delegation seems to follow a "rational" pattern if the image was relatively "easy" to classify. Note that we chose the threshold of 70% consistently over the following studies; as no image had an average accuracy between 0.7 and 0.717, setting the threshold to the precise average accuracy of 0.717 does not lead to any changes. Effect sizes and significance levels are in Table 3. Why did humans delegate randomly if images were hard?

In the next section, we present Study 2, which explores possible explanations related to the boundary conditions of successful delegation as potential mechanisms for the observed phenomenon.

Table 2. Study 1 Summary of p-Values for Pairwise Comparisons of Accuracy

Condition	Humans alone	Delegation	Inversion
AI	<0.001	<0.001	<0.001
Humans alone		0.120	<0.001
Delegation			<0.001

Figure 3. Scatter Plot of Accuracy per Image (Horizontal Axis) Against Delegation Rate per Image (Vertical Axis), Where the Regression Line Is Estimated from All Images



3.3. Study 2: Explaining and Enforcing a Delegation Strategy

3.3.1. Hypotheses. This study seeks to analyze the cognitive challenges in human delegation and aims at providing assistance to explore potential paths toward more productive delegation. In the previous study, we observed random delegation patterns for hard images. Our boundary conditions of successful delegation lead to different possible explanations that we test in this study:

1. Humans might not have a sufficient level of metaknowledge. To be able to analyze this, we asked humans to self-report their level of certainty for each image in all conditions.

2. Humans might not be able to come up with a good delegation strategy. We added a condition where we advised humans with a strategy that imitates the inversion logic.

3. Humans might not be willing to delegate sufficiently. We added a condition where delegation was enforced based on human certainty; this condition applies inversion with humans.

Consequently, Study 2 contains three conditions, all allowing the option to delegate to the AI: a "baseline" condition that replicates the delegation condition of Study 1 asking for self-reported certainty for each image, a "strategy explained" condition where we suggest a delegation strategy that imitates the delegation logic of inversion based on human certainty, and a "strategy enforced" condition where we enforce a strategy by automatically delegating images to the AI if a human reports low certainty. As was the case in

Figure 4. Scatter Plot of Accuracy per Image (Horizontal Axis) Against Delegation Rate per Image (Vertical Axis), Where the Two Regression Lines Are Estimated from Two Partitions of the Data

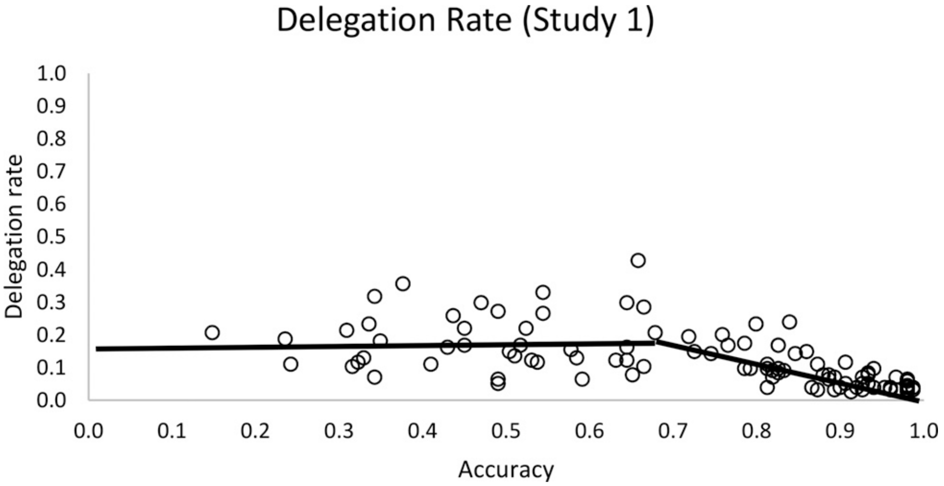


Table 3. Study 1 Regression Results for Delegation (Dependent Variable: *Delegation rate*)

	Accuracy of …	
Variable	< 70%	≥ 70%
Accuracy	0.029	−0.535***
	(0.104)	(0.067)
Constant	0.169***	0.557***
	(0.052)	(0.059)
Observations	41	59
R^2	0.002	0.529
Adjusted R^2	−0.024	0.521
Residual SE	0.090 (df = 39)	0.038 (df = 57)
F-statistic	0.080 (df = 1; 39)	64.138*** (df = 1; 57)

Note. Standard errors are in parentheses.
***$p < 0.01$.

Study 1, we preregistered two initial hypotheses based on classification accuracy.

Assuming that all three explanations of inferior human delegation performance apply, we state two hypotheses. First, if humans are simply unaware of good delegation strategies, they should improve if such a delegation strategy is suggested. Thus, we pose our first hypothesis.

Hypothesis 2.1. *Explaining the delegation strategy leads to a slight improvement in accuracy.*

If humans are reluctant to delegate, then enforcing a good strategy should increase accuracy even stronger than just suggesting it, which leads to our second hypothesis.

Hypothesis 2.2. *Enforcing the strategy leads to a stronger improvement in accuracy.*

In the following, we present the detailed experimental design and the results of Study 2.

3.3.2. Design. In this study, we compare three between-subjects conditions. We also asked humans to report their level of certainty for each image on a scale from 1 (uncertain) to 4 (certain) in all conditions. The baseline condition was set up like the delegation condition of Study 1. For the remaining two conditions, we propose a simple delegation rule similar to that of the AI in the inversion condition, where (1) it assessed its classification certainty and (2) delegates to humans if the certainty score was below average human performance. Accordingly, we advised subjects in the second condition, strategy explained, to delegate images for which they were uncertain (certainty levels between 1 and 3; average accuracy expected to be below the AI performance of 0.77). If subjects' certainty was high (certainty level 4; average accuracy expected to be above the AI performance of 0.77), we advised them to classify the image themselves. In the third condition, strategy enforced, subjects could not delegate actively. We informed them that images will be delegated automatically if their self-reported certainty was between 1 and 3. The human answer was only considered if the reported score was a 4. This condition represents most closely the human version of our inversion condition of our first experimental study.

We recruited 453 subjects via MTurk and randomly assigned them to experimental conditions. Average pay was $5.19; average duration was 56.2 minutes. The assignment process and experimental protocol was equivalent to that of Study 1.

3.3.3. Results. Table 5 shows summary statistics for accuracy and delegation rates. Accuracy improved slightly, and delegation rates increased strongly when the delegation strategy was explained or enforced. Delegation rates in the strategy enforced condition look similar to the strategy explained condition. This suggests that humans, indeed, followed the suggested delegation rule.

This is supported by statistical analysis. A Levene's test reveals no significant differences between the variances across experimental conditions ($F(2, 450) = 0.849$, $p = 0.429$), but means are different (ANOVA, $F(2, 450) = 2.97$, $p = 0.052$, $\eta^2 = 0.13$, which represents a medium effect). All pairwise comparisons are summarized in Table 4. Tukey's significance test shows that humans in the strategy enforced condition outperform humans in the baseline condition. This difference (2.714 percentage points) is significant ($p = 0.048$) and represents a small to moderate effect ($d = 0.281$). Mean accuracy in the strategy explained condition is similar to that in the strategy enforced condition ($p = 0.761$). Also, the difference between the strategy explained group and the baseline group (1.913 percentage points) is not significant ($p = 0.207$). It would represent a small effect ($d = 0.185$). When comparing the conditions' accuracies with AI performance, the baseline condition shows a significantly lower performance ($p = 0.010$), but there is no significant difference between AI and the strategy explained ($p = 0.727$) or the strategy enforced condition ($p = 0.484$). In total, engaging with a good delegation strategy led to more delegation, but accuracy did not increase proportionally. We also compute the accuracy of humans per (self-reported)

Table 4. Study 2 Summary of *p*-Values for Pairwise Comparisons of Accuracy

Condition	Baseline	Strategy explained	Strategy enforced
AI	0.010	0.727	0.484
Baseline		0.207	0.048
Strategy explained			0.761

Table 5. Study 2 Summary Statistics for Accuracy and Delegation Rate

Condition	*N*	Min	Mean	Max	SD	25th pctl	Median	75th pctl
				DV: *Accuracy*				
Baseline	150	0.160	0.748	0.900	0.104	0.720	0.770	0.810
Strategy explained	157	0.240	0.767	0.880	0.103	0.750	0.800	0.825
Strategy enforced	146	0.140	0.775	0.900	0.088	0.750	0.790	0.823
				DV: *Delegation rate*				
Baseline	150	0.000	0.131	0.680	0.151	0.010	0.080	0.200
Strategy explained	157	0.000	0.342	0.950	0.203	0.185	0.330	0.475
Strategy enforced	146	0.010	0.335	0.960	0.183	0.190	0.315	0.463

Note. DV, dependent variable; pctl, percentile.

certainty score. From pretests, we expected the accuracy for images with certainty scores between 1 and 3 to be below 0.77 and for images with a certainty score of 4 to be above 0.77. Our results validate this assumption: for condition 1, the average accuracies for non-delegated images were 0.43 (certainty score 1), 0.52 (certainty score 2), 0.68 (certainty score 3), and 0.87 (certainty score 4).

Figure 5 shows the delegation pattern. The horizontal axis depicts image difficulty (average human accuracy of condition 1, as defined in Study 1), the vertical axis delegation rates. The baseline condition replicated the results of Study 1. Furthermore, humans delegated more when the strategy was explained or enforced. However, their behavior for difficult images was still random. The randomness just centered on a higher average than in the baseline condition. Therefore, knowing a good delegation strategy did not prohibit random delegation of difficult images. Hence, we can rule out the second explanation from the preceding: although providing a strategy helps to increase delegation, it could not fix the random delegation pattern for difficult images. Table 6 shows the corresponding statistical results.

We now address the third explanation (humans do not want to use the AI). We analyzed how delegation rates changed with perceived image difficulty (i.e., self-assessed certainty). Figure 6 plots delegation rates (vertical axis) against self-assessed certainty (horizontal axis). The figure suggests that humans delegated with great internal consistency. Images they perceived as more difficult were delegated more often. This was true independent of whether or not they knew the delegation strategy. The subjects appeared to be aiming for a consistent delegation pattern. Once they learned a good delegation strategy, delegation rates more than doubled. Therefore, we conclude that in our experiments, humans did not show reluctance toward using the AI.

In light of these findings, the first explanation seems likely. Humans might not be able to judge the difficulty of images when the images are hard. They may thus not be able to use the AI systematically for these images, a problem associated with a lack of metaknowledge.

To explore this explanation, we study how well humans can assess their own ability to classify images. In Figure 7 we plot the average self-assessed certainty of an image (vertical axis) against the average accuracy of the image (horizontal axis). The visual impression and the regression results in Table 7 suggest that humans can assess their ability for relatively easy images (accuracy above 70%), but they cannot assess it for difficult images. An interesting side finding can be observed for the strategy enforced condition. Here, the constant of the regression model is positive and significant for easy images. Thus, objective difficulty explains perceived difficulty (as in the other conditions), but subjects seem to report higher certainty values independent of actual image difficulty. A possible

Figure 5. Study 2 Scatter Plots of *Accuracy* Against Delegation Rate per Image and Experimental Conditions, Where the Two Regression Lines Are Estimated from the Two Partitions of the Data

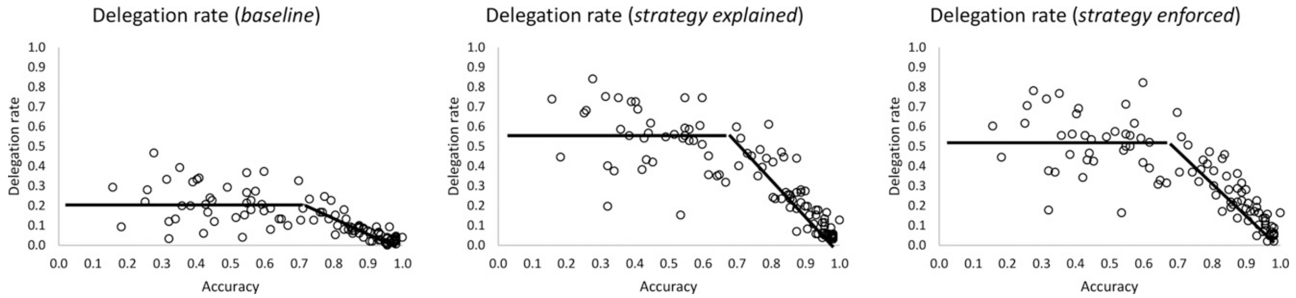
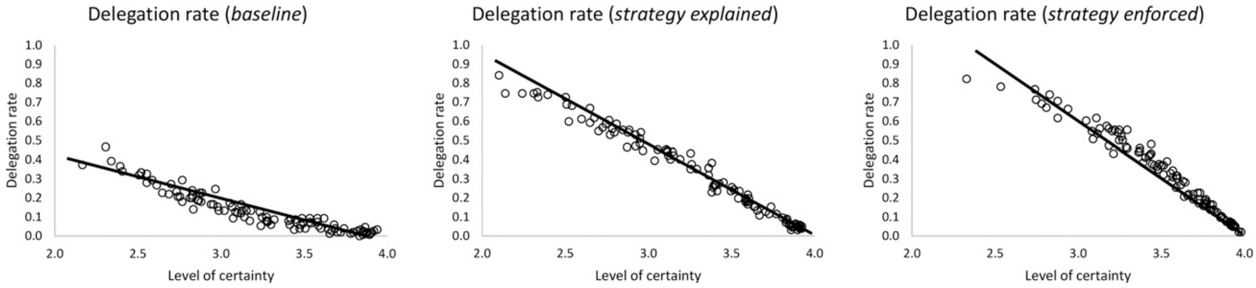


Figure 6. Study 2 Scatter Plots of *Certainty* Against Delegation Rate per Image and Experimental Conditions



explanation is that subjects avoided automated delegation by (mis)reporting certainty values of 4.

Therefore, although humans delegate quite rationally based on their internal assessment (Figure 6), this assessment is not precise for relatively difficult tasks (Figure 7). Put differently, although human delegation decisions are often misaligned with real problem difficulty, they are not misaligned with their perceived problem difficulty. We conclude that the lack of metaknowledge seems to drive the inferior delegations. According to this explanation, humans did not know what they knew and delegated the wrong images to the AI.

4. Robustness Checks

In this section, we test the robustness of our findings with two additional studies. In the first robustness check, we analyze whether continuous feedback on both human and AI performance has an impact on delegation behavior and human metaknowledge. In the second robustness check, we test whether an AI could realize complementarities with humans, even in cases where the tasks are more difficult than those the AI was trained with. We manipulate task difficulty by scaling the images to a lower resolution and test the effectiveness of inversion.

4.1. Study 3: The Role of Feedback

4.1.1. Purpose. Study 3 relaxes the assumption of receiving no feedback on task results to analyze the effects of feedback on human delegation behavior and on human metaknowledge.

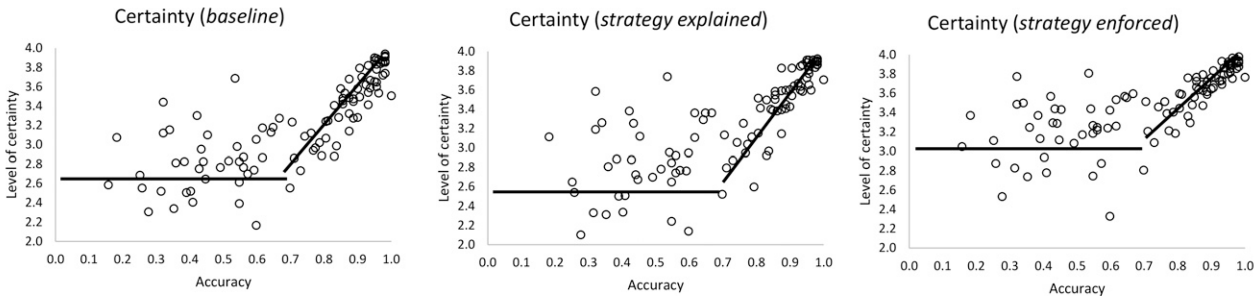
At the outset, we would like to point out that the potential effects are unclear, ex ante, and the literature provides no clear direction. We lay out possible effects in the following discussion. First, metaknowledge might be increased by providing continuous feedback because it could improve the human perception with regard to the person's own performance. However, we observe that even long-term experience does not seem to prevent poor metaknowledge (Brezis et al. 2018). Thus, the effect remains unclear. Second, feedback on human and AI performance might increase salience of AI superiority and could consequently lead to higher delegation rates. On the other side, Dietvorst et al. (2015) demonstrate that humans relied less on algorithmic advice after seeing it err, even if the algorithmic performance was superior. Thus, we do not state any directional hypotheses in this study. In the following, we lay out the details of our study design before presenting our results.

Table 6. Study 2 Regressions per Experimental Condition (Dependent Variable: *Delegation rate*)

	Baseline		Strategy explained		Strategy enforced	
	Delegation rate of images, with accuracy of …					
	< 70%	≥ 70%	< 70%	≥ 70%	< 70%	≥ 70%
Accuracy	−0.041	−0.588***	−0.230	−1.610***	−0.131	−1.486***
	(0.121)	(0.072)	(0.182)	(0.165)	(0.180)	(0.142)
Constant	0.233***	0.592***	0.650***	1.626***	0.579***	1.520***
	(0.060)	(0.064)	(0.090)	(0.146)	(0.090)	(0.126)
Observations	41	59	41	59	41	59
R^2	0.003	0.537	0.039	0.625	0.013	0.657
Adjusted R^2	−0.023	0.529	0.015	0.619	−0.012	0.651
Residual SE	0.105	0.041	0.158	0.094	0.157	0.081
F-statistic	0.117	66.08***	1.59	95.14***	0.531	109.30***

Notes. The data are partitioned into two regions. Standard errors are in parentheses.
$^{***}p < 0.01$.

Figure 7. Study 2 Scatter Plots of *Accuracy* Against Certainty per Image and Experimental Conditions



4.1.2. Design.

We compare classification accuracy and delegation rate between two conditions. The baseline condition (condition 1) replicates the delegation condition of Study 1 and the baseline condition of Study 2. In the "feedback" condition (condition 2), subjects received feedback after each classification task, consisting of their own answer, the AI answer, and the correct answer. We ran a between-subjects design with 289 subjects in February 2021, and we randomly assigned subjects to the baseline condition (148 subjects) and the feedback condition (141 subjects).

All subjects received instructions, had to pass a short quiz so that we could exclude bots, and completed an example classification to ensure they understood the task. They then had to classify the 100 images in random order. Each subject received a base fee of $2 and an additional $0.05 for each correct answer. Afterwards, subjects were asked how many images they think they classified correctly. They could earn an additional dollar if this estimation did not differ from the actual number by more than five images. The average pay was $4.92, slightly above average pay on MTurk in general (Hara et al. 2018). The average duration of the experiment was 62.7 minutes.

4.1.3. Results.

Descriptive statistics (see Table 8) show little difference among the experimental conditions, regarding both accuracy (baseline: 53.4%, feedback: 54.4%) and delegation rate (baseline: 12.0%, feedback: 12.4%). Accuracy does not significantly differ in the baseline and the feedback conditions ($p = 0.697$); neither does the delegation rate ($p = 0.860$). Thus, there is no indication that continuous feedback on human and AI performance affects human delegation behavior. Note that, in line with literature on MTurk performance during COVID-19 (Arechar and Rand 2021), the average accuracy values are below those of our previous studies, whereas delegation rates remain similar.

Next, we analyze the effect of continuous feedback on metaknowledge by replicating the analysis of the relationship between accuracy and certainty in Study 2. We illustrate the relationship of delegation rate and difficulty (average human accuracy of condition 1, as defined in Study 1) in Figure 8. We further summarize the regression results in Table 9: as in Study 2, we only see a significant influence of "difficulty" (measured by the average accuracy of each image) for images with an average accuracy of at least 70%. Note that we use the average accuracy of the first condition of Study 1, where humans classified without AI delegation, to maintain a consistent definition of "easy" and "difficult" tasks.

In the next section, we present a robustness check on the impact of more difficult tasks on the efficiency of delegation and inversion.

Table 7. Study 2 Regressions per Experimental Condition (Dependent Variable: *Certainty*)

	Baseline		Strategy explained		Strategy enforced	
	Subjects' certainty of images (per image), with accuracy of...					
	< 70%	≥ 70%	< 70%	≥ 70%	< 70%	≥ 70%
Accuracy	0.249	3.524***	0.368	3.505***	0.109	2.363***
	(0.384)	(0.344)	(0.465)	(0.374)	(0.384)	(0.238)
Constant	2.716***	0.383	2.675***	0.453	3.161***	1.608***
	(0.191)	(0.304)	(0.231)	(0.332)	(0.191)	(0.211)
Observations	41	59	41	59	41	59
R^2	0.011	0.648	0.016	0.606	0.002	0.633
Adjusted R^2	−0.015	0.642	−0.009	0.599	−0.024	0.626
Residual SE	0.334	0.196	0.403	0.214	0.334	0.136
F-statistic	0.419	105.10***	0.626	87.64***	0.081	98.25***

Notes. The data are partitioned into two regions. Standard errors are in parentheses.
***$p < 0.01$.

Table 8. Study 3 Summary Statistics for Accuracy and Delegation Rate

Condition	*N*	Min	Mean	Max	SD	25th pctl	Median	75th pctl
				DV: *Accuracy*				
Baseline	149	0.070	0.534	0.880	0.221	0.373	0.540	0.758
Feedback	141	0.070	0.544	0.950	0.232	0.340	0.620	0.750
				DV: *Delegation rate*				
Baseline	149	0.000	0.120	1.000	0.231	0.000	0.010	0.120
Feedback	141	0.000	0.124	0.990	0.212	0.000	0.010	0.155

Note. DV, dependent variable; pctl, percentile.

4.2. Study 4: The Role of Difficulty

4.2.1. Purpose. Inversion was the most effective condition in our first experimental study. The key to its success was the AI's ability of assessing its own quality. Study 4 confronts the AI with tasks that are more difficult than those it was trained with. In the case of image classification, this could relate to images with a lower resolution. Thus, we replicate Study 1 with a higher task difficulty by applying a lower resolution to all images. We aim to analyze whether the AI would still be able to delegate efficiently.

4.2.2. Design. We compare classification accuracy between two conditions, "humans alone" (condition 1) and "delegation" (condition 2). Those conditions mirror the two conditions of Study 1. We further use condition 1 to simulate different inversion strategies. We ran a between-subjects design with 299 subjects in January 2021 and randomly assigned subjects to the humans alone condition (150 subjects) and the delegation condition (148 subjects).

All subjects received instructions, had to pass a short quiz so that we could exclude robots, and completed an example classification to ensure they understood the task. They then had to classify the 100 images in random order. Each subject received a base fee of $2 and an additional $0.05 for each correct answer. Afterward, the subjects were asked how many images they think they classified correctly. They could earn an additional dollar if this estimation did not differ from the actual number by more than five images. The average pay was $4.61, slightly above average pay on MTurk in general (Hara et al. 2018). The average duration of the experiment was 65.9 minutes.

4.2.3. Results. Humans slightly improve by about three percentage points (Table 10) with the possibility to delegate ($p = 0.093$), even though, on average, only 7.6% of images were delegated. Although no direct comparison is possible, we see that the human performance does not seem to be strongly affected by lower resolution, as the total accuracy seems to be similar to those of Study 3. AI performance, however, was decreased significantly from 77% to 54%. Human performance still remains below AI accuracy. Next, we analyze whether the AI is still able to improve by delegating to humans, even though its own performance dropped strongly. In Figure 9, we simulate inversion accuracies based on the humans alone condition with varying threshold values. A threshold of 0 symbolizes always choosing the AI prediction resulting in the AI accuracy of 54%, whereas a threshold of 1 symbolizes always choosing the human prediction resulting in the average human accuracy of 48.1%. With every threshold value below 0.95, the inversion accuracy outperforms both human and AI accuracy, with a maximum value at a threshold of 0.50, close to the average human accuracy. Using an inversion

Figure 8. Study 3 Scatter Plots of *Accuracy* Against Certainty per Image and per Experimental Conditions, Where the Two Regression Lines Are Estimated from the Two Partitions of the Data

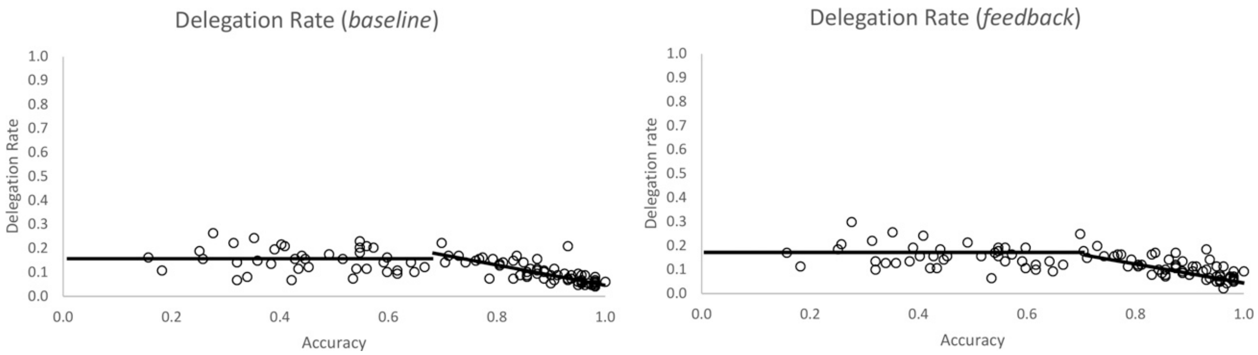


Table 9. Study 3 Regressions per Experimental Condition (Dependent Variable: *Certainty*)

	Baseline		Feedback	
	Subjects' certainty of images (per image), with accuracy of...			
	< 70%	≥ 70%	< 70%	≥ 70%
Accuracy	0.099	1.527***	0.182	1.372***
	(0.179)	(0.238)	(0.134)	(0.205)
Constant	3.130***	2.067***	3.083***	2.148
	(0.089)	(0.210)	(0.067)	(0.205)
Observations	41	59	41	59
R^2	0.008	0.420	0.045	0.439
Adjusted R^2	−0.018	0.410	0.021	0.430
Residual SE	0.156	0.136	0.116	0.117
F-statistic	0.305	44.33***	1.09	44.67***

Notes. The data are partitioned into two regions. Standard errors are in parentheses.
***$p < 0.01$.

delegation rule with a threshold of 0.50 improves the human accuracy by 15 percentage points and the AI accuracy by 9 percentage points. Thus, even in a situation where the AI performs relatively poorly, inversion seems to be a powerful delegation mechanism.

5. Discussion and Directions of Future Research

Our results demonstrate that humans and AI can work together on image classification, even if there is no feedback about the AI performance and errors. In such a situation, it is beneficial to let the AI delegate work to humans in case the AI is uncertain. Humans were unable to delegate well. We claim that the reason for their wrong delegation decisions is that the human subjects were unable to assess if they know the correct class of difficult images. This result is interesting because it shows inferior human performance but no aversion to use the algorithm. Our data support the explanation that subjects were indeed motivated to work with the machine and were willing to follow rational delegation strategies. They were unable to execute those because of their wrong perception of task difficulty. We interpret this as a fundamental and latent limitation rather than as an act of conscious reluctance. In this regard, our results are consistent with the general view issued in Logg et al. (2019): humans do appreciate the help from AI. But we also show that they might still have problems working with it.

Furthermore, our results challenge the assumption that an entire task should be handed over to an AI if the AI is better. We stated three boundary conditions where delegation and a good distribution of work can outperform the assignment to one party. First, humans and AI have to have complementary skills. We claim this should be the case for tasks where decision rules are not clearly defined. We confirm this using image classification as an example: an optimal combination of the AI and humans from the inversion condition would lead to an average accuracy of 89.9%, considerably more than 77% accuracy for AI alone and 71.7% for humans alone. Second, complementarities have to be recognized. We define a sufficient level of metaknowledge as a necessary condition. Although the AI seems to have a good perception of its own abilities, humans are not able to differentiate between tasks they are able to do and those where this is not the case, especially for difficult images. Third, an efficient delegation rule needs to be followed, where a task is moved to the actor better able to solve it. Under perfect information, a simple rule is effective: if you are able to do the task, do it yourself; if you are not, then delegate. We demonstrate that such a rule can easily be implemented for AI and that humans can potentially be trained to follow such a rule.

5.1. When AI Delegates to Humans: Inversion

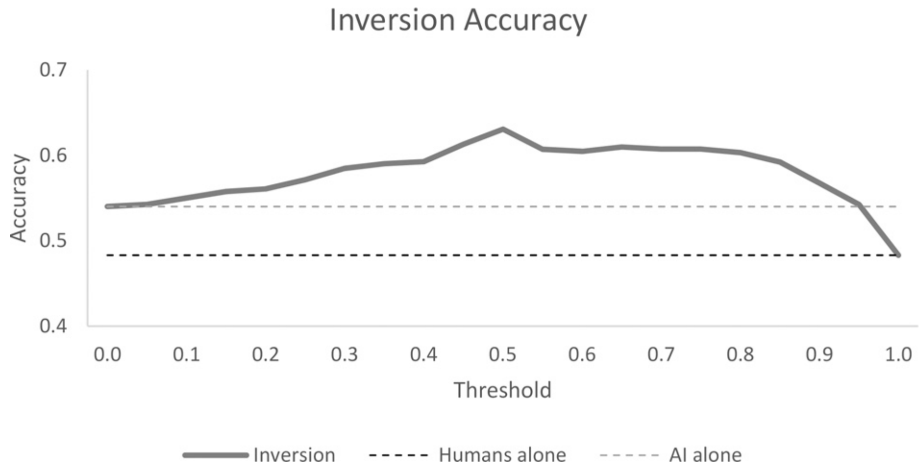
If AI would be responsible to delegate to humans, several interesting things could happen. First, in our experiment, the resulting performance was higher than that of the AI alone. This makes inversion economically desirable. Second, humans would do some of the work. They contribute to the superior result; without

Table 10. Study 4 Summary Statistics for Accuracy (Dependent Variable: *Accuracy*)

Condition	N	Min	Mean	Max	SD	25th pctl	Median	75th pctl
Humans alone	150	0.120	0.481	0.790	0.168	0.360	0.480	0.633
Delegation	148	0.140	0.512	0.790	0.153	0.420	0.510	0.630

Note. pctl, percentile.

Figure 9. Inversion Accuracy by Threshold Value



them, we would not reach it. Inversion might also improve human work perspectives. Humans are more motivated when working in a stimulating environment (Pink 2011). In our example, classifying easily identifiable images is perhaps routine and boring, whereas the classification of difficult images could be an interesting challenge. Inversion might enable humans to spend less time on mundane tasks and more time on challenging tasks, thereby creating a more fulfilling workplace. Thus, receiving assignments from a machine could be interpreted not only as a delegation to humans but also as freeing humans from tedious tasks. The AI would not be the humans' boss but rather an assistant who swipes away distractions from the real work. However, inversion comes with a loss of human control. The AI decides about the delegations; it asks the human for support only if it is required. It does this without emotions, only to leverage complementarities that exist as foreseen by Polanyi's groundbreaking work.

5.2. When Humans Delegate to AI: Metaknowledge and the Quest for Good Delegation

Our research points to a fundamental characteristic of human behavior that needs to be understood in order to design more effective human–AI collaborative environments: humans did not perform well in delegating tasks to the AI. We can design and teach simple delegation rules, especially in modularized tasks. However, even when humans diligently and rationally apply a delegation rule (Figure 5) that is internally consistent with their perception of task difficulty, humans who delegate to an AI do not perform as well as they should. The reason for this (Table 9) is an apparent lack of understanding of what is difficult for them and what is not. This phenomenon is not isolated to working with AI or computers. Humans tend to misjudge their certainty when dealing with highly difficult questions compared with questions of medium difficulty or easier (Pulford and Colman 1997). In our research context, this translates into humans making more arbitrary delegation decisions when dealing with difficult tasks, which worsens their overall performance.

More generally, the phenomenon to not understand the difficulty of a task at hand relates to a lack of metaknowledge in terms of "appreciation of what we do know and what we do not know" (Russo and Schoemaker 1992, p. 8). In our formal education, we do not emphasize this higher level of learning to recognize our own strengths and shortcomings. Often, the impact of lacking metaknowledge when facing difficult issues is mitigated by team work, when other human group members point out alternatives, logical and procedural inconsistencies, and/or errors. One way to interpret group discussions is to try and achieve the best compromise based on metaknowledge and primary knowledge based on facts, concepts, models, relationships, and solution techniques. However, humans working with AI are unlikely to be in an environment where they can reason with AI or, more specifically, where AI engages humans in a dialogue to resolve issues related to metaknowledge. If we want to produce students that will be effective in the future workforce, improving metaknowledge should be a central tenet of higher education.

5.3. Limitations

Our study informs on delegation between humans and AI. To ensure a certain degree of generalizability of results, we aimed for a generic, nonspecialized task and nonspecialized workers relying on image classification and MTurk workers. Although we think that our findings carry over to many other settings, there might be additional effects in any specialized environment that strengthen or weaken our findings. Although relying on nonspecialized situations is a limitation of this study, it also creates an opportunity for future research and to test whether our findings can be replicated in specialized environments.

There has been a lot of discussion on the suitability of MTurk workers for behavioral experiments. These discussions concentrate on three main criticisms of using MTurk in behavioral experiments: First, nonnaïveté—that is, subjects might be experienced in similar experiments and behave strategically (Chandler et al. 2019). Second, carelessness—that is, subjects act with a lower degree of rigor leading to noisy and partially inconsistent results (Aruguete et al. 2019). Third, representativeness—that is, the MTurk population does not reflect the composition of society in general. However, it should be noted that MTurk subjects are better representatives of the general population compared with typical student subjects used in a large number of academic studies (Chandler et al. 2019).

How could we safeguard against these issues? We contend that nonnaïveté does not apply in this instance because our study is unique in character, compared with, for example, potentially hundreds of studies looking at newsvendor problems or dictator games. A potential solution could be to rely on new MTurk workers or to exclude workers who participated in similar studies if this information is available. We excluded all subjects who participated in our own related studies or pretests. In terms of the carelessness of MTurk workers, Aruguete et al. (2019) show some evidence of carelessness in terms of a higher spread in data quality in MTurk samples compared with traditional student samples and recommend measures to ensure validity of results. Following these suggestions, we decided to (a) restrict our subject pool to subjects with a positive track record and at least 90% positive reviews and (b) include an attention check and a classification exercise that had to be passed without errors in order to participate in the study. Please note that for our set of robustness experiments (Studies 3 and 4), we had to conduct the experiments during the COVID-19 pandemic. This led to an increased level of subjects' carelessness and lower performance compared with the other studies. This finding is in line with the literature (Arechar and Rand 2021), and we refrain from direct comparisons of the specific results between the first set of experiments and the robustness checks. We admit that our study does not claim to represent a general population. Thus, we do not make any claims regarding absolute results of our study, such as "we expect humans to delegate 13% of tasks to an AI"; rather, we compare differences in behavior between conditions. Replicating several studies from different subject samples with MTurk samples, Coppock (2019) conclude that MTurk samples can be compared with other national samples. Many other studies validate the appropriateness of MTurk samples for experimental studies in social sciences, such as Buhrmester et al. (2016), Horton et al. (2011), and Lee et al. (2018).

5.4. Future Research

As laid out in the preceding, a potentially relevant limitation of our sample lies in an expected low performance, especially for the samples drawn during the COVID-19 pandemic. In concert with focusing on nonspecialized tasks, this limits the generalizability of the results regarding the absolute performance of our experiment. Although we do not expect that those limitations have affected our main findings regarding different configurations of delegation schemes, or the mechanisms we observed, we believe that analyzing similar settings with high-impact decisions and dedicated workers is a fruitful avenue for future studies.

In addition to addressing potential limitations of our study, a key research area should focus on making humans better delegators in order to develop effective human–AI collaborative environments. This requires research on three fronts:

1. *Research on human–AI dialogue and decision authority:* How should an AI engine communicate and adapt when working with humans that have different levels of metaknowledge, and how should it develop an appropriate framework for decision making in these environments? For example, an AI engine can delegate decision authority to individuals with high levels of metaknowledge, whereas it may simply receive inputs from highly competent individuals lacking metaknowledge.

2. *Research on system feedback to increase metaknowledge:* Prior research (Pulford and Colman 1997) has shown that feedback may not affect metaknowledge, especially when the task is difficult. No concerted effort has been made to design feedback environments that lead to improved individual metaknowledge when other options are available.

3. *Research on improving metaknowledge*: Laboratory studies have shown that experience only partially impacts metaknowledge (Hansson et al. 2008), and our robustness check in Study 3 showed no effect of providing continuous feedback on metaknowledge. We still cannot rule out that long-term debriefing—for example, as is common with airline pilots (Kikkawa and Mavin 2017)—might improve metaknowledge by providing humans with a better understanding of their own strengths, weaknesses, and boundaries. This may lead to better appreciation of alternative sources that can help in making decisions. In human-only environments, providing long-term feedback and intensive debriefing is costly. Human feedback may show internal consistency problems and may be intrusive at the task level. However, modern technology, including realistic simulations (see Ketter et al. (2016) as an example), can

potentially provide innovative solutions that help improve our metaknowledge.

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