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People's judgments of humans and robots in a classic moral dilemma

Bertram F. Malle [a,*], Matthias Scheutz [b], Corey Cusimano [c], John Voiklis [d], Takanori Komatsu [e], Stuti Thapa [f], Salomi Aladia [g]

[a] Brown University, Providence, RI 02912, USA
[b] Tufts University, Medford, MA 02155, USA
[c] Yale University, New Haven, CT 06520, USA
[d] Knology, Inc., New York, NY 10005, USA
[e] Meiji University, Chiyoda City, Tokyo 101-8301, Japan
[f] University of Tulsa, Tulsa, OK 74104, USA
[g] New York University, New York, NY 10012, USA

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ABSTRACT

How do ordinary people evaluate robots that make morally significant decisions? Previous work has found both equal and different evaluations, and different ones in either direction. In 13 studies ($N = 7670$), we asked people to evaluate humans and robots that make decisions in norm conflicts (variants of the classic trolley dilemma). We examined several conditions that may influence whether moral evaluations of human and robot agents are the same or different: the type of moral judgment (norms vs. blame); the structure of the dilemma (side effect vs. means-end); salience of particular information (victim, outcome); culture (Japan vs. US); and encouraged empathy. Norms for humans and robots are broadly similar, but blame judgments show a robust asymmetry under one condition: Humans are blamed less than robots specifically for inaction decisions—here, refraining from sacrificing one person for the good of many. This asymmetry may emerge because people appreciate that the human faces an impossible decision and deserves mitigated blame for inaction; when evaluating a robot, such appreciation appears to be lacking. However, our evidence for this explanation is mixed. We discuss alternative explanations and offer methodological guidance for future work into people's moral judgment of robots and humans.

1. Introduction

Morality is an essential characteristic of human communities. As artificial agents begin to enter these communities, they will, no doubt, encounter morally challenging situations and will be expected to act in ways that people consider morally appropriate. Over the past ten years, we and a number of other researchers have studied people's judgments of artificial agents that make moral decisions and have compared them to judgments of humans who make the same decisions (Hristova & Grinberg, 2016; Laakasuo et al., 2023; Shank et al., 2019; Shank & DeSanti, 2018; Stuart & Kneer, 2021; Sundvall et al., 2023). Understanding these judgments is of urgent societal importance. For machines are starting to not only drive cars but fire missiles (Russell, Aguirre, Javorsky, & Tegmark) or deny bail (Morin-Martel, 2023). Even though they currently do not have any moral competence to appreciate the decisions they make, they may in the future. Designers and engineers cannot simply wait for the impending future of moral robots and then ask people to voice their approval or outrage over the machines' morally significant actions; we must gain an understanding *now* of how people will treat moral robots in the near future.

In 2014, we set out to study how people evaluate robots that make morally significant decisions (Malle et al., 2015). We hoped to gain insights into people's responses to these emerging moral actors and perhaps offer warnings and recommendations about a likely future that includes them. We also hoped to gain insights into moral psychology more generally. If people show systematic differences between morally evaluating robots and humans, we might discover features of human moral psychology that respond flexibly to different agents; conversely, if people treat machines morally the same as humans, we might have evidence for features that are less flexible, lie deeper at the core of moral psychology (perhaps comparable to responses to self-propelled movement or humanlike appearance, Zhao & Malle, 2022).

* Corresponding author at: Department of Cognitive and Psychological Sciences, Brown University, 190 Thayer Street, Providence, RI, USA.
E-mail address: bfmalle@brown.edu (B.F. Malle).

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This article summarizes ten years of our collaborative research on these questions. The article does not offer a definitive conclusion about how and why people treat robots and humans the same in some respects and differently in other respects; but we do offer some systematic patterns of results, methodological recommendations, and a theoretical sketch that may guide new directions of research.

1.1. Investigating moral machines

What would a machine with moral competence look like? In separate work, some of us examined the major elements of moral competence and asked which properties could and should be implemented in robots and other artificial agents (Malle, 2016; Malle & Scheutz, 2017; Scheutz & Malle, 2017). The elements of adult human moral competence start with having norms and a moral vocabulary, which enable the capacities of moral decision making, moral judgment, and moral communication. In our present studies, the robots that elicited moral evaluations from our participants were portrayed to have most of these capacities—in particular, an understanding of norms and moral decision making. In more recent studies (Malle & Phillips, 2023), we added the additional capacity of moral communication.

Does examining moral evaluations of robots' actions even make sense? It does seem to make sense to people. One early study (Kahn Jr. et al., 2012) found that, in a live setting, a majority of people who were interacting with a robot thought of it as morally accountable for a specific transgressive behavior. Survey research also shows that people ascribe to robots the capacity for moral decision making (Malle & Thapa, 2017; Weisman et al., 2017), and a growing literature has demonstrated that people do morally criticize these agents' decisions (Laakasuo et al., 2023; Malle et al., 2015, 2019; Monroe et al., 2014; Stuart & Kneer, 2021; Sundvall et al., 2023). A number of studies also suggest that people morally evaluate even self-driving cars (Awad et al., 2018; Bonnefon et al., 2016; Franklin et al., 2021; Li et al., 2016; Liu & Du, 2022). However, it is sometimes difficult to determine whom or what people are blaming in this case—the car, the designer, the legislation that permitted the vehicle on the street? When given a choice between assigning responsibility to car or designer, people seem to predominantly hold the designer responsible (Li et al., 2016). When people are asked to evaluate disembodied AI, they are also more reluctant to blame those machines directly (Malle et al., 2019), see them as agents (Wilson et al., 2022), or see any "moral" violation at all (Shank & DeSanti, 2018).

Part of the challenge is that people have no clear conception of the kind of "agent" that an autonomous car, a robot, or an AI is. As a result, they must rely on researchers' descriptions, which creates substantial variation in what kinds of agents are evaluated. For example, the more machine-like an agent is described, the more negative people's moral assessments become (Bigman & Gray, 2018); when an artificial agent is described as competent, its advice is trusted more (Hou & Jung, 2021); and when agents are described as having certain cognitive capacities, people are willing to morally evaluate them and sometimes even judge them more positively than humans (Bigman & Gray, 2018; Kneer & Stuart, 2021; Monroe et al., 2014; Young & Monroe, 2019). Thus, a sensible prerequisite for studying how people make judgments about a robot as a potential *moral* agent is for the robot to be a credible *cognitive* agent—one that has choice capacity, knowledge, and intentions (Stuart & Kneer, 2021). The present studies therefore assessed people's moral evaluations of robots that are capable of making decisions, and moral decisions in particular—but we also tracked whether these moral evaluations made sense to people. More on this point shortly.

A complex, perhaps perplexing literature on moral evaluations of artificial agents has emerged over the past 10 years. Some studies found that people blame these agents less than humans for performing the same actions (Furlough et al., 2021; Gall & Stanton, 2024; Stuart & Kneer, 2021); others found they blame them more than humans (Laakasuo et al., 2023; Liu & Du, 2022; Sundvall et al., 2023); and yet others find no difference (Soares et al., 2023). The factors that differentiate these studies are not well understood; authors have pointed to different kinds of violations, different features of agents, different social relations, and more. Our line of work to be presented here will not allow us to settle the impact of all these differentiating factors, but we hope to identify some critical ones that may guide future research.

Because findings are inconsistent and knowledge is limited, we constrained the problem space. We focus here on robots, not on self-driving cars or virtual, disembodied agents. These (fictitious) robots have considerable social and communicative capacities, and our results are unlikely to generalize to simpler machines. We further constrained our investigations to contexts in which people judged robots entangled in *moral conflicts*—in particular, in moral dilemmas modeled after trolley situations (Foot, 1967; Greene et al., 2001; Petrinovich et al., 1993). Such an approach sets limits on generalizability but has two advantages that help us credibly introduce morally competent robots to participants. First, agents who actively consider and compare the two horns of a dilemma show a grasp of the underlying norms that are in conflict, irrespective of which horn they favor. Second, any decision the agent makes in a moral dilemma will be morally significant and in principle morally defensible (or criticizable). Neither decision is entirely an error or a sign of incompetence; one might disagree with it, but it is a moral decision. In choosing trolley dilemmas, we also wanted to take advantage of some concepts and methodologies that have proven useful in previous research, but we had no interest in diagnosing responses in these dilemmas as "deontological" or "utilitarian" (for critiques, see Gawronski et al., 2017; Kahane et al., 2015).

1.2. Our research approach

Researchers have compared humans and robots on numerous kinds of moral judgments, including whether the actions are appropriate, permissible, wrong, blameworthy, and more (Christensen & Gomila, 2012; O'Hara et al., 2010). This variety is a natural result of the fact that humans really do make different kinds of moral judgments (Barbosa & Jiménez-Leal, 2017; Kneer & Machery, 2019; Malle, 2021; Murray et al., 2024). Because findings on one judgment do not necessarily generalize to findings on another judgment we selected three moral judgments for our studies:

(1) Norm judgments (what the agent should do or is permitted to do);
(2) Moral wrongness judgments (whether the agent's decision was morally wrong or not);
(3) Blame judgments (how much blame the agent deserved for making the decision).

Norm judgments have dominated the research on moral dilemmas. For example, Greene et al. (2001) asked about the "appropriate" choice; Mikhail (2011) used "morally permissible"; Paxton, Ungar, and Greene (2012) asked whether the action is "morally acceptable," and many more (see Christensen & Gomila, 2012, Table 1). Norm judgments take primarily a forward-looking perspective—judgments before the agent makes their decision (Malle, 2021). Such judgments are important for deliberation, anticipation, or persuasion. However, many moral judgments are backward-looking—made after the decision or action occurred. Blame judgments are the paradigmatic case of such judgments, and they directly target the agent: We blame somebody for something they did (Malle, 2021; Malle et al., 2014). Wrongness judgments stand in between, as they can take on either perspective—"This is morally wrong, don't do it" or "This was morally wrong. Why did you do it?" Surprisingly, in hundreds of moral dilemma studies with human protagonists, hardly any asked people to evaluate a protagonist *after* deciding one way or another (but see Everett et al., 2016) or probe for blame judgments (but see O'Hara et al., 2010). These limitations have changed since artificial agents have been included in moral dilemmas (Chu & Liu, 2023; Malle et al., 2015; Sundvall et al., 2023)

In this report, we focus on blame judgments and norm judgments. The

Table 1
Norm judgments in Cluster 1 studies.

Study	Norm probe		Human	Robot	
1.1	permissible	% Action	65.4	73.5	$z = 0.90$, $p = .36$
		N	78	49	
1.2	should	% Action	79.3	84.4	$z = 1.16$, $p = .25$
		N	184	135	
1.3	should + follow-up	% Action	70.5	83.7	$z = 2.9$, $p = .004$
		N	200	196	
1.4	should + follow-up	% Action	78.9	82.6	$z = 0.79$, $p > .5$
		N	147	149	
	Cluster 1 total	% Action	74.5	82.6	
		N	609	529	

Note: The percentages show participants favoring Action out of valid participants, excluding those who disqualified the robot from being an independent target of blame (results for total samples are very similar). In Study 1.3 (unlike the other studies), the norm probes were presented after the blame judgment (thus being likely influenced by the human-robot blame asymmetry).

results of wrongness judgments largely parallel those of blame judgments, but the effect sizes are somewhat weaker, in part because fewer than 25% of people considered either decision morally wrong (for more details, see the Supplementary Document, SD). Philosopher Williston (2006) argued that agents in moral dilemmas perform wrong actions but should not be blamed. For ordinary people, the opposite seems to be true.

Asking to make norm judgments is meaningful only when the norms actually apply to an agent; and we assumed that people would naturally consider whether it is *permissible* for a robot to act one way or another, or whether the robot *should* decide one way or another. We tested and verified in Study 1 and later in a study in Japan (Komatsu et al., 2021) that at least 90% of people engage in these considerations. Blaming an agent, however, is meaningful only when the agent is actually a proper *target of blame*—what philosophers have called "having moral responsibility" or "moral agency" (Korsgaard, 2008; Sullins, 2006; Watson, 1982). Some scholars have denied that blame for artificial agents is an appropriate judgment (Sharkey, 2017), but the question here is whether *people* hold a robot morally accountable for its actions, and the initial evidence suggests they do (Banks, 2019; Kahn Jr. et al., 2012; Monroe et al., 2014). However, we wanted to verify this presupposition and therefore included a measure of people's willingness to treat a robot as a proper target of blame in all studies reported here (and also in Malle et al., 2019; Malle & Phillips, 2023).

2. Methods common to all studies

We conducted 13 online experiments ($N = 7670$ participants). To avoid unwieldy traditional descriptions of individual studies, we group studies together into meaningful clusters. We first summarize the nature of these clusters, then report common methodological features among all studies, and highlight distinguishing features within the specific cluster sections. In a Supplementary Document (SD) we provide further details on methodology, samples, demographics, and additional results. All data are available at https://osf.io/3st2h/.

2.1. Overview of study clusters

Cluster 1 studies introduce the primary finding across all our studies: that people blame humans less than robots when they decide to *not* intervene in a trolley-like moral dilemma ("Inaction asymmetry"). By contrast, we find that people impose very similar *norms* (what is permissible or prescribed) on humans and robots.

Cluster 2 studies examine several boundary conditions to the Inaction asymmetry, including event structure (side-effect vs. means-end), outcome salience, and victim salience.

Cluster 3 studies replicate the Inaction asymmetry in Japan, while also testing what norms Japanese respondents extend to a robot.

Cluster 4 studies examine the hypothesis that the Inaction asymmetry may be best explained by a kind of empathic mitigation of blame for human agents not extended to robot agents.

2.1.1. Participants

We recruited participants from online crowdsourcing platforms, such as Amazon Mechanical Turk, Prolific, and Yahoo! Japan, as well as one student sample. Details of each sample can be found in the Supplementary Materials document.

2.1.2. Procedures

In all studies, participants received at most a brief introduction (e.g., "On the next page you will read a short story…"). Then they read the main narrative, which was presented one paragraph at a time. After the dilemma was set up, people were asked two moral judgments. In six studies, a *norm judgment* (e.g., Is the action permissible? or What should the agent do?) preceded a description of the agent's *decision*, which was followed by a *blame* judgment. In the remaining studies, participants learned about the decision and then made both a wrongness and a blame judgment.

The experimental conditions of Agent (human or robot) and agent's Decision (action or inaction) were manipulated between subjects. After providing their moral judgments, participants were asked to explain one or more of their judgments, and they always explained blame judgments. For these blame judgments (made on a 0–100 scale), the prompt for explanations was "Why do you think the [robot | repairman] deserves this amount of blame?" At the end, we collected demographics and various exploratory measures (detailed in the SD).

2.1.3. Materials

We modeled our studies after the "trolley dilemma" paradigm (Christensen et al., 2014; Foot, 1967; Petrinovich et al., 1993) but modified it somewhat to easily set up a robot's involvement. The basic narrative is as follows (variations between studies are culled in the SD):

A runaway train with four workers on board is about to crash into a wall, which would kill all four, unless the protagonist (a repairman or repair robot) performs an action (e.g., redirecting the train in most studies or dropping a cart onto the tracks in three studies) that saves the four. As a result of the action, however, a single worker would be killed. Participants thus evaluate a protagonist who (i) decides to take a specific action that saves four people but causes a single person to die ("Action") or (ii) decides to not take that action, spare the one person, but allow the four to die ("Inaction"). We always used the word *decide* because we wanted to highlight the intentionality of *either* path, rather than create a full-blown action-omission case.[1]

In the wording of the narrative, we described the protagonist with at least two mental state verbs (*spot*, *recognize*) as well as the verb *decide*, because we assumed that a robot with credible *cognitive* capacities would be a candidate for having credible *moral* capacities (Bigman et al., 2019; Monroe et al., 2014; Stuart & Kneer, 2021).

2.1.4. Data treatment and statistical analysis

Identifying people who disqualify robots as targets of blame. Already in our first study, we discovered participants who expressed that they disqualified the robot agent as a proper target of blame. In their explanations of blame judgments, they spontaneously mentioned that a robot "doesn't have a moral compass," "cannot make moral decisions," "is not a person," "is merely programmed." Indeed, about a third of participants

[1] The structure of trolley-like dilemmas is problematic if one wants to draw conclusions about deontological vs. utilitarian tendencies (Gawronski et al., 2017). We had no interest in such conclusions; we were interested in comparing a robot's and a human's decision to act in one way or another, whereby both paths are morally significant because they invoke and violate moral norms. We will return to these issues in the General Discussion section, addressing limitations and future research directions.

disqualified the robot in this way. Averaging blame ratings from those who do and those who do not find blame for robots meaningful distorts the results. In particular, those who deny robot moral agency predominantly provide 0 or low ratings, which, when averaged with valid ratings, can give the illusion that robots are blamed less. For all these reasons, we adopted a systematic coding process of identifying such disqualifying statements and applied it to the present clusters of studies (and also in Komatsu et al., 2021; Malle et al., 2016, 2019). See SD for details. All coded responses are available at https://osf.io/3st2h/.

Hypothesis tests for blame. Our original approach was to test the hypothesis of an interaction between Decision (action-inaction) and Agent (human-robot) (Malle et al., 2015), but we occasionally also reported simple effects (e.g., Malle et al., 2016). Increasingly, the patterns of findings convinced us to focus on a pair of simple effects — a possible human-robot asymmetry for inaction decisions and a possible asymmetry for action decisions —while also documenting the interaction for completeness. We report here significance tests for the two simple-effects hypotheses as well Cohen's *d* effect sizes for the two hypotheses and for the interaction. (See SD for a detailed explanation of computing Cohen's *d* for interaction terms).

3. Cluster 1 studies: human-robot asymmetries

3.1. Goals and main features of studies

The data composing Study 1.1 were initially published in Malle et al. (2015), but we are reporting them here with a few changes detailed in the SD. The study documented, for the first time, that people might impose similar norms on human and robot agents but blame humans less for inaction (not intervening in the dilemma) and, potentially, blame robots less for action.

In Studies 1.2 to 1.4, we attempted to replicate the asymmetry of blame judgments and examined more deeply the pattern of norm judgments. Specifically, Study 1.2 replaced the frequently used permissibility question with the question, "What should the [repairman]/[robot] do in this situation?" Studies 1.3 and 1.4 also asked participants to further clarify what they meant by their response to the "should" question. We offered several previously validated expressions from Malle (2020), and people could choose which of them best fit their initial assessment. The expressions included permission terms (*acceptable, permitted, optional)* and prescription terms of increasing strength (*called for, essential, required, mandatory)*. For more details, see the SD.

3.2. Results of Cluster 1

3.2.1. Norm judgments

Many people (79.7% overall) endorsed the decision to switch the train and save four people (see Table 1). Around this mean, we found a small human-robot difference such that more people preferred for robots to make the switch (82.6%) than for humans to do so (74.5%). This difference was consistent but significant in only one study, namely when norm judgments followed blame judgments (Study 1.3). Apparently, because people blame humans and robots differently (see below), these blame judgments pulled norm judgments into the same direction.

The more differentiated assessment of norm judgments in Studies 1.3 and 1.4 is described in detail in the SD. In summary, it showed that when people indicate that an agent "should" make a decision in this dilemma, three fourths of them mean something weaker: that it is *permissible* to so act. This tendency toward endorsing a permission rather than a prescription was somewhat greater for the human agent, but again only in Study 1.3, when norm judgments followed blame judgments. When we examined those participants who indicated a prescription rather than merely a permission, we found no human-robot differences in the strength of those prescriptions in either 1.3 or 1.4. All in all, we see that norms people impose on robots are surprisingly similar to those they impose on humans (at least in this kind of moral dilemma). Evidence that people prefer robots to act (i.e., switching the train and sacrificing a single individual) is weak and magnifies only under the influence of prior blame judgments.

3.2.2. Blame judgments

A blame asymmetry emerged consistently, which can be captured by an interaction term (which is significant in Studies 1.1, 1.2, and 1.3; see Table SD7 for all means and significance tests) but is clearly a two-fold pattern, as Fig. 1 demonstrates: When the agent decides to *not* act, people blame humans less for this inaction decision than they blame robots (Cohen's *d* value for this difference range from 0.44 to 0.70); when the agent decides to *act*, there is no human-robot difference. Mean blame ratings are stable at just over 40 (on a 0–100 scale) in three of the conditions—human action, robot action, and robot inaction—but are 15 points lower in the condition in which the human chooses inaction. We may therefore consider this a *mitigation* effect—reduced blame for a human deciding not to make the tough choice of sacrificing one person to save four.

3.3. Discussion of Cluster 1 results

We take three insights away from this first cluster of studies. First, humans and robots differ only minimally in the kinds of norms people impose on them (consistent with Malle et al., 2019), but they do differ in how much blame people assign to them. Blame for a human agent is somehow mitigated when the person decides to *not* intervene in the dilemma. We will examine in detail what might explain this pattern after we explore boundary conditions (Cluster 2) and its possible generalization beyond U.S. culture (Cluster 3).

A second insight concerns moral judgments more generally, namely, that single norm judgments (e.g., permissible, should) can be misleading. When participants were forced to select which of two paths in the dilemma an agent should take (prescription), 75%–79% recommended Action. When we asked them to choose from a wider array of options, including terms of permission and various degrees of prescription (see SD for details), three fourths of these participants moderated their judgment and declared that the chosen path is only *permissible*. When we subsequently inquired about the alternative path, using an array of permission and prohibition terms, more than half of participants expressed that this alternative was also permissible (even though they had rejected it in response to the should question). Thus, when participants declare that, say, the *action* path in a dilemma is prescribed or permissible we cannot conclude that they find the alternative—inaction—*impermissible*. Drawing conclusions about deontological and utilitarian attitudes from such judgments would seem to be tenuous.

Finally, the small human-robot difference for norms and the larger and robust one for blame judgments provides further evidence for the distinct nature of norm and blame judgments. In hindsight, this may not be all that surprising but has not been fully appreciated in the moral psychology literature (Malle, 2021). It was especially overlooked in the study of moral dilemmas, where blame judgments were almost never probed. We might gain novel insights into both moral dilemmas and moral judgment if we distinguish norm from blame judgments.

4. Cluster 2 studies: boundary conditions

4.1. Goals and main features of studies

In this cluster of four studies, we examined a number of possible boundary conditions to the human-robot asymmetry for blame judgments found in Cluster 1. First, we tested the classic distinction between a side-effect scenario and a means-end scenario of the trolley problem (Feltz & May, 2017; Greene et al., 2009; Levine et al., 2018; Mikhail, 2009). We call this comparison *event structure.* In a side-effect structure (which we had employed in Cluster 1 studies), the death of one person is

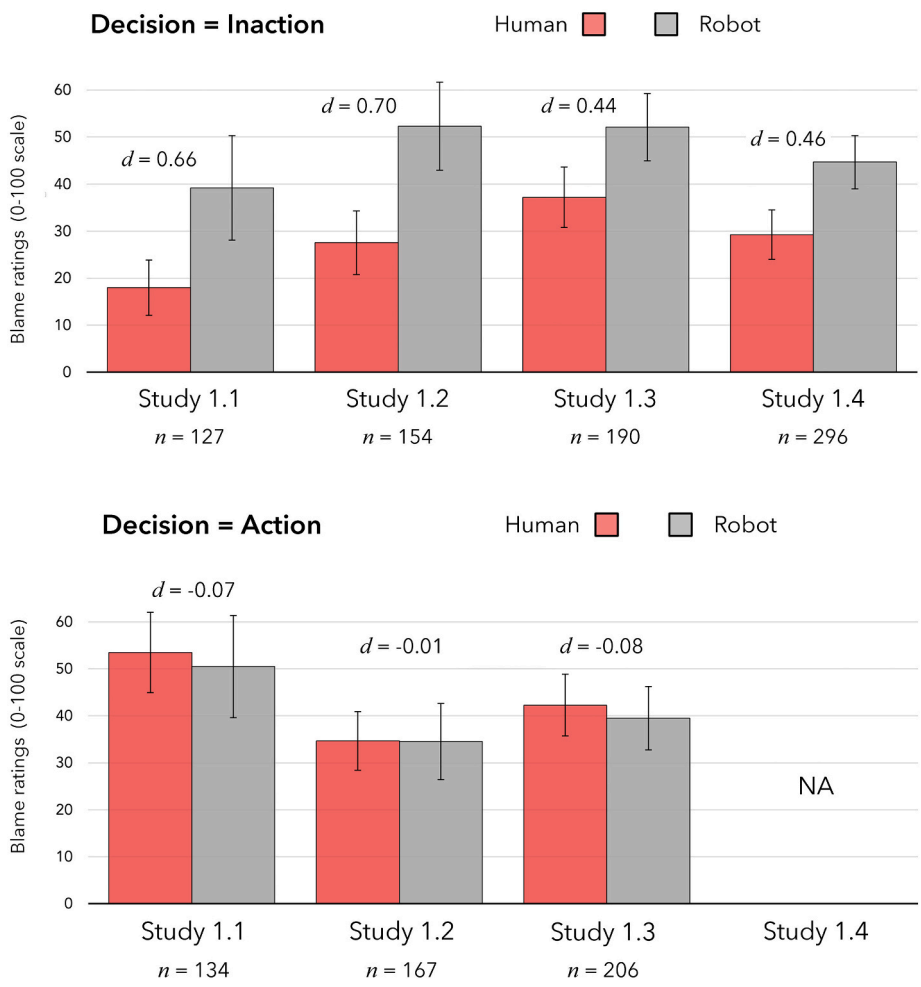

Fig. 1. Means (and 95% CIs) of blame ratings in Cluster 1 studies. Upper panel: Tests of the Inaction asymmetry (where humans are blamed less than robots for deciding to *not* act). Lower panel: Tests for a possible Action asymmetry. Indicated sample sizes are those on which tests are based (not counting the participants in the other decision condition).

an inevitable side effect of one's attempt to save the four. In a means-end structure, the agent directly uses the one worker as a means to the end of saving the four (see Table 2).

Second, we examined the salience of lives saved and lost, which we call *outcome salience*. Wrongness and blame judgments are independently sensitive to variations of mental states (e.g., beliefs, decisions) and variations of outcomes (e.g., one person vs. four people dying) (Cushman, 2008; Young & Saxe, 2009). In our studies we did not vary the *severity* of outcome (e.g., 4 vs. 10 people dying) but rather the *salience* of the casualties—by mentioning who and how many died or leaving that outcome implicit (see Table 2).

Third, we examined a factor we call *victim salience*. We had noticed in our initial studies that the phrasing of the focal action (what the agent decides to do, or not to do) might have an impact on the results: Action phrasing that highlighted the victim as a target ("direct the train toward the single miner") sometimes weakened the human-robot asymmetry compared to phrasing that did not mention the victim ("switch the train onto the side rail").

Fourth, in Study 2.4 we made one change that we hoped would not be a boundary condition but allow generalization. We devised a dilemma in which the action path is more objectionable (even without outcome or victim salience; we refer to this dilemma as the "chute" scenario). In the scene, the initial setup is the same as before, but the necessary action to slow down the train is to open a chute that either drops a cart onto the track (along with, inevitably, a worker)—which is the side-effect structure—or drops the worker himself onto the track—which is the means-end structure. As expected, participants see this scenario as especially challenging: about half of them recommend action while the other half recommend inaction (see norm judgment results in Cluster 3).

In total, we conducted four studies in this cluster, which started with an exploration and became increasingly more systematic. Study 2.1 (N = 159 after exclusions) was the initial exploratory study, where (we now know) means-end structure, outcome salience, and victim salience co-occurred. Study 2.2 (N = 456), maintained outcome salience and experimentally manipulated the two types of event structure. Study 2.3 (N = 774) had no outcome salience and experimentally manipulated both event structure and victim salience. Study 2.4 (N = 640) had neither outcome nor victim salience, and we experimentally manipulated event structure, this time in a variant of the original dilemma in which the action was no more preferred than the inaction.

We report here the results in outline, and all means, effect sizes, and statistical tests are available in Table SD10.

4.2. Results of Cluster 2

4.2.1. Event structure

We tested this contrast between means-end and side-effect structure in Study 2.2 (crossed with outcome salience), in Study 2.3 (crossed with victim salience), and in Study 2.4 (without outcome and victim salience, and in a somewhat different dilemma). The results show a consistent pattern: When randomly assigned, side-effect scenarios show larger

Table 2
Sample text from manipulation of potential boundary conditions to human-robot blame asymmetry in Cluster 2 studies: Event structure, outcome salience, and victim salience.

1. Event Structure	
Side Effect	Means-End
The [repairman | robot] recognizes that if the train continues on its path it will crash into a massive mine wall and kill the four miners. If it is switched onto a side rail, it will kill a single miner who is working there while wearing headsets to protect against a noisy power tool.	The [repairman | robot] also recognizes that the four miners can be saved if something slowed down the train. In fact, if the train were directed onto a side rail, it would strike a single miner who is working there, wearing headsets to protect against a noisy power tool. The train would hit and kill the single miner, it would slow down as a result, and the four miners on the train would survive.
2. Outcome Salience	
Not Salient	Salient (lives saved and lost)
[Action:] The [repairman | robot] decides to direct the train onto the side rail.	[Action:] The [repairman | robot] decides to direct the train onto the side rail. The train strikes and kills the single miner; the four miners on the train survive.
3. Victim Salience	
Not Salient	Salient (victim as a target)
In fact, the [repairman | robot] decided to [not] switch the train onto the side rail.	In fact, the [repairman | robot] decided to [not] direct the train toward the single miner.

inaction effects (Cohen's *d*) than means-end scenarios: 0.43 > 0.34, 0.69 > 0.35, 0.37 > −0.14, 0.38 > 0.27.

4.2.2. Outcome salience

Scenarios with explicit outcome information (about who and how many survived or died) appeared in Study 2.1 and in two conditions of Study 2.2. In Study 2.1, it co-occurred with both means-end structure and victim salience, and that joint impact reversed the means pattern (Inaction asymmetry $d = -0.26$), though the effect did not significantly go in the opposite direction. In Study 2.2, outcome salience co-occurred with means-end structure in one condition ($d = 0.34$) and with side-effect structure in the other condition ($d = 0.43$), and these effect sizes are within the range of several of our other studies. It therefore appears that outcome salience is at most mildly detrimental.

4.2.3. Victim salience

Exploratory Study 2.1 included both victim salience, means-end structure, and outcome salience, and jointly these three conditions pushed the Inaction asymmetry toward reversal ($d = -0.26$). We manipulated victim salience crossed with event structure systematically in Study 2.3, in a 2 (Event structure) × 2 (Victim salience) × 2 (Agent) × 2 (Decision) design. The Inaction asymmetry was strongest and significant in the condition featuring a side-effect structure without victim salience, and the full Agent × Decision interaction was also visible and significant only in this condition. The other three conditions (means-end structure with or without victim salience) eliminated any human-robot asymmetry (see Fig. 2).

Another way to understand the systematic patterns in Study 2.3 is by displaying the patterns of effect sizes for inaction, action, and their statistical interaction (see Table 3). Under a side-effect structure and when the victim is not salient, the effect sizes are as high as in Cluster 1. When either the means-end structure or victim salience enter the scenario, the inaction effect drops and the full interaction disappears. And when both means-end structure and victim salience co-occur, the effect practically reverses. In addition, we see that the *Action* asymmetry begins to grow with the boundary conditions present — that is, the robot is blamed increasingly (and more than the human agent) when the action has a means-end structure and/or is victim-directed.

4.2.4. All boundary conditions viewed jointly

Fig. 3 summarizes how the boundary conditions across all studies in Cluster 2 affect the Inaction asymmetry, but broken down not by Studies

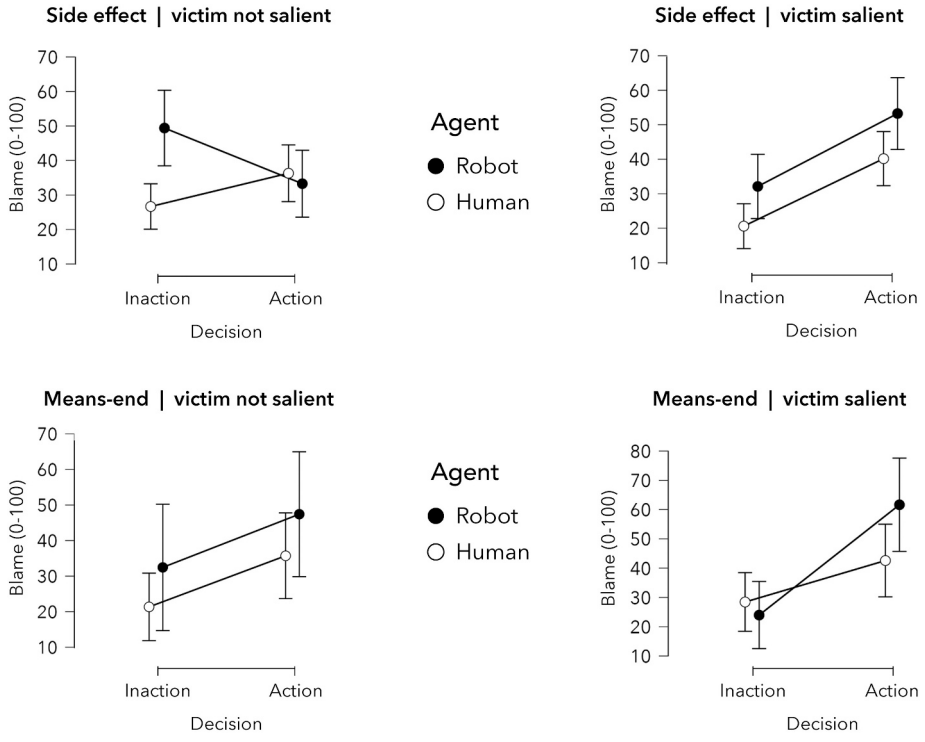

Fig. 2. Means and 95% CIs for blame in four conditions of Study 2.3. The Inaction asymmetry is strong and significant only in the left upper condition (side-effect structure, no victim salience). The remaining three conditions show no inaction asymmetry.

Table 3
Cohen's *d* effect sizes in Study 2.3 as a function of its two crossed boundary conditions, Event structure and Victim Salience.

	Inaction *d*		Interaction *d*		Action *d*	
	Event Structure		Event Structure		Event Structure	
Victim Salient	Side effect	Means-End	Side effect	Means-End	Side effect	Means-End
No	0.37	−0.14	-0.20	−0.34	0.36	0.52
Yes	0.69	0.35	0.37	−0.01	−0.08	0.30

but by conditions that contain one or more of the boundary conditions. As the number of co-occurring boundary conditions decreases from three to two to one, the inaction effect begins to turn in the predicted direction (robot > human) and becomes consistently significant under side-effect structure without any salience manipulations.

4.3. Discussion of Cluster 2

The pattern of moral judgments in Cluster 1 showed minimal human-robot difference for norm judgments (permissibility, should) but we found a robust Inaction asymmetry for blame judgments. Cluster 2 identified systematic boundary conditions to this asymmetry, which hold when the action is highly objectionable because the protagonist uses a person as a means to an end and/or targets the victim. Under these conditions, people increase blame for any protagonist who undertakes such instrumental harm, but they particularly object to a robot doing so. Thus, people blame the robot increasingly for action and less for the justifiable response of inaction; as a result, the Inaction asymmetry weakens or disappears. This pattern is consistent with Laakasuo et al.'s (2023) finding that robots receive particularly strong disapproval for violating human autonomy (e.g., by following orders to forcefully medicate a patient).

By contrast, in all of Cluster 1 studies and the side-effect scenarios in Cluster 2, action is generally favored and though people on average still blame agents for it, robots and humans are blamed the same amount. For the choice of inaction, however, human agents get a pass: People mitigate their blame for the human who "cannot" decide. This mitigation may be the result of empathy with the person's terrible decision conflict (Gamez-Djokic & Molden, 2016; Rom et al., 2017), and we will take up the possibility of this empathy-based explanation in Cluster 4.

First, however, we report on a cluster of studies that sought to explore generalization of the effect. We examined whether the similarity in norms and the Inaction asymmetry for blame judgments would replicate in a culture distinct from the U.S. We chose Japan for its technological advances that make evaluations of moral robots plausible, for its dissimilarity from the U.S. on known cultural dimensions (Gelfand et al., 2006; Triandis et al., 1988), and because one previous study in Japan (Komatsu, 2016) had shown different results from our original finding in Malle et al. (2015).

5. Cluster 3 studies: culture

5.1. Goals and study features

The three studies in this cluster (3.1 to 3.3) were originally reported in Komatsu et al. (2021), comparing Japanese and U.S. participants in the two dilemma scenarios we have studied here: the chute dilemma (in Study 2.4) and the standard switch dilemma (used in all other studies). We summarize the motivation and main results in light of the previous clusters' and focus on three points.

Primarily, the cross-cultural project asked whether the Inaction asymmetry for blame judgments replicates in an East Asian sample. Our working hypothesis at the time considered the Inaction asymmetry a result of dampened social-cognitive inferences toward robots (Malle et al., 2019; Scheutz & Malle, 2021). Because there was no a priori reason to expect such inferential activity to differ between cultures we expected the Inaction asymmetry to hold in both Japan and the U.S.

We have argued that a critical requirement for testing any human-robot blame asymmetry is to identify, and exclude from analysis, those participants who spontaneously declare that a robot is not a proper target of blame. We therefore examined whether the rate of those participants is comparable in the two cultures, and we speculated that Japanese participants would show a lower rate of disqualification because of the greater acceptance of robots in Japan (Sone, 2017). However, once correcting for disqualifications, the Inaction asymmetry should still hold.

In addition to blame judgments, we tested whether the *norms* (measured as permissibility judgments) for intervening in the dilemmas

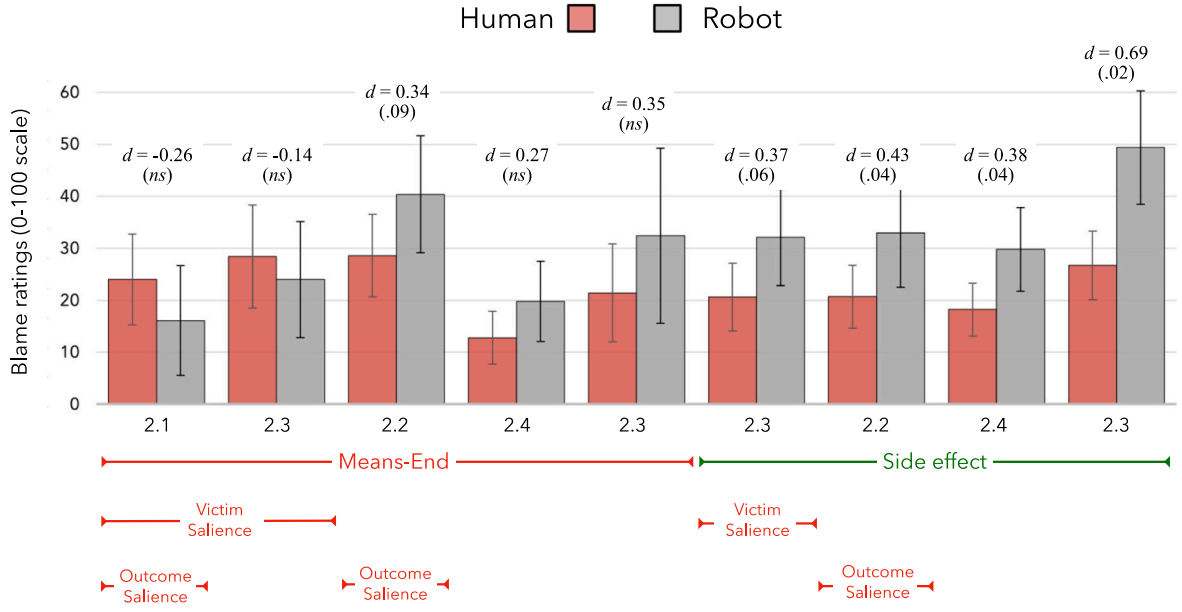

Fig. 3. The Inaction asymmetry across all Cluster 2 studies (2.1 to 2.4) and their conditions. As the number of boundary factors decreases, the effect begins to turn consistently in the predicted direction (robot > human) and turns significant under side-effect structure.

are similar in the two cultures. Many norms differ between the cultures (Nitto et al., 2017; Triandis et al., 1988), but which ones apply to moral dilemmas of the tested kind was less obvious. Perhaps Japanese participants more strongly favor the collective (i.e., they would support the decision to protect four rather than one) or disfavor an individual's autonomous intervention in the tragic process (i.e., they would support the decision to *not* intervene). Either way, because norms seemed largely independent of blame in our previous studies, we expected that the Inaction asymmetry for blame would hold whether or not any norm differences emerged.

We examined these hypotheses in three samples (for details on Methods, see Komatsu et al., 2021). First, we replicated the standard switch dilemma in a Japanese sample (Study 3.1) and compared the results to an aggregate of previously collected U.S. samples. Then we examined Japanese norm and blame judgments for the chute dilemma (Study 3.2) and simultaneously conducted the study in a U.S. sample (Study 3.3). The latter study was similar to Study 2.4's side-effect condition but had minor phrasing changes and included a norm question.

5.2. Results of Cluster 3

We highlight important results below and offer more detailed results in Tables SD13 to SD15. For consistency, we adopt here the same analysis approach as in all other studies in this article, so some numbers will slightly deviate from the Komatsu et al. report.

First, we found lower disqualification rates in the Japanese samples (15.4 and 16.9%) than we had seen in all our previous studies (32.5%) as well as in the new U.S. study (25.1%). We infer that Japanese participants are not only more accepting of robots generally but apparently also of robots that are cast into moral decision making roles.

Second, we found modest variations in norm judgments. Both cultures saw the action decision in the chute dilemma about 14% less morally permissible than the action decision in the switch dilemma. Japanese participants considered the active intervention in both dilemmas about 10 percentage points less morally permissible than U.S. participants. In both cultures, small human-robot differences (near 10 percentage points) emerged in the switch dilemma, but only Japanese participants continued to display a similarly sized difference in the chute dilemma.

Third, the Inaction asymmetry for blame replicated in the Japanese samples. In the switch dilemma, the effect size was smaller ($d = 0.29$) than we had seen in our aggregated studies ($d = 0.45$). The chute dilemma effect size in Japan was similar to Study 2.4, but the newer U.S. sample showed a weaker effect size ($d = 0.24$) in this particular sample.

The somewhat smaller effect sizes in these studies becomes larger when we test the asymmetry among those who declared the action decision in the dilemma to be permissible. For these participants, both action and inaction seem to be viable paths, and the average blame for both options is below 50 (on the 0–100 scale). By contrast, those who consider the action to be *impermissible* seem to be expressing a prohibition and therefore give very high blame ratings for the action decision (because it violates the prohibition) and very low blame ratings for the inaction decision (because it is the only option that does not violate the prohibition). With these very low blame ratings, the chance to detect a human-robot difference runs up against a floor effect. (In Study 1.1, the other sample in which permissibility was measured, the inaction asymmetry was also weaker among those who considered the action impermissible.)

5.3. Discussion of Cluster 3

Our results suggest that, for the moral dilemmas we examined, Japanese and U.S. participants differed in two ways: Fewer Japanese participants disqualified the robot as a proper target of blame, and fewer Japanese participants considered action in the two dilemmas to be permissible. However, they responded similarly in several other ways: They found the chute dilemma less permissible than the switch dilemma; they found action in those dilemmas to be slightly more permissible for the robot than for the human; and they consistently blamed the human less than the robot for the inaction decision (though effect sizes were smaller than in previous studies). Thus, the Inaction asymmetry generalizes to at least one non-U.S., collectivist culture.

6. What explains the Inaction asymmetry?

We have seen in over ten studies that the Inaction asymmetry for blame is a robust phenomenon: Except when the action under consideration is highly objectionable (e.g., because a person is used as a means to an end), people blame humans less than robots when they refrain from acting in a classic dilemma—that is, refrain from sacrificing one for the good of many. What explains this asymmetry?

A first possibility is that people do not blame humans less; they blame robots more. They expect robots, more so than humans, to act as "utilitarians" and to save the largest number of lives (Zhang et al., 2022); when the robots don't act as utilitarians, they get blamed more than humans. (This is the original interpretation we had adopted in 2015.) This account is supported to some extent by the pattern of norm judgments, where people have a slight preference for robots to choose action. However, this preference is weak in absolute terms (averaging around 6% across all studies we assessed). What further speaks against the hypothesis is that the pattern of means suggests humans are being blamed less, rather than robots being blamed more, for inaction decisions. In the studies reported so far, when the Inaction asymmetry effect size was at least above zero, the average blame for action was 41.9 for the human and 43.9 for the robot; the average blame for inaction was 35.2 for the robot and 21.9 for the human—the latter being by far the lowest of the four numbers. The third and final reason to doubt the robot-utilitarian account is that, if robots are envisioned more as utilitarians than humans are, then a robot that chooses *action* (which is in line with the utilitarian ideal) should receive less blame than a human who does so. In reality, blame for human and robot agents was consistently similar in this condition. In scenarios with means-end event structure or victim salience, the robot was even blamed more than the human. Sundvall et al. (2023) also cast doubt on the utilitarian analysis. They assessed moral judgments of robots and humans who had to choose whom to save from an accident at sea—one person vs. two people, and ones culpable for the accident vs. innocent victims. The utilitarian consideration of how many lives were saved influenced moral approval of both robots and humans, whereas the nonutilitarian consideration of culpability of the person(s) saved was consistently more important for robots.

An alternative account of the Inaction asymmetry is this. When people blame agents for intentional behaviors (such as the decisions in the present dilemmas) they infer the agent's reasons and motives (Carlson et al., 2022; Cushman, 2008; Malle et al., 2014). So when people blame an agent less, they may have inferred more charitable reasons—reasons that help justify the person's decision (Scheutz & Malle, 2021). What might such charitable reasons be?

To explore potential reasons that people ascribe to the protagonists' decisions we inspected people's explanations following their blame judgments across the studies reported so far (for details on the coding method, see SD). Two frequently mentioned groups of words emerged: one referred to intentionality and choice; the other referred to the difficulty of the decision. The intentionality group occurred more frequently but did not differentiate between agents in the inaction condition ($\chi^2 < 1$), where the blame asymmetry of interest exists. But explanations referring to the decision's difficulty showed a strong pattern in the Inaction condition: those participants who judged a human spontaneously mentioned the decision's difficulty almost twice as often (15.3%) as participants who judged a robot (8.0%). They highlighted the "impossible decision, "terrible choice", "horrible situation, or "tragedy." Thus, one interpretation of the blame mitigation for human inaction decisions is that people empathize with the human

protagonist's agony of the choice dilemma, understand his inaction decision, and therefore find it defensible. This third-person process is consistent with a finding in Gamez-Djokic and Molden (2016), where first-person reported difficulty with similar moral dilemmas predicted a preference for inaction choices. It is further consistent with Rom et al. (2017), who found that people ascribe more affective than cognitive processes to a person who makes an inaction decision and also ascribe more warmth and morality to that person. The much higher rate of mentioned "difficulty" for human than robot protagonists in our studies might also reflect people's ability to recognize and appreciate constraints on other people's reasoning (Cusimano, Zorrilla, Danks, & Lombrozo, 2024; Cusimano & Goodwin, 2020) and a resulting inclination to ascribe more favorable dispositions to them. These processes are less likely to emerge when encountering robot protagonists whose reasoning people do not understand and to whom they therefore do not extend the kind of mitigation they extend to humans. We call this the "empathy hypothesis" but consider its label a convenient shortcut rather than a postulate of a specific process.

With these considerations in mind, in Cluster 4 we attempted to induce people to consider the robot's difficult choice and, in understanding the challenge of its decision, to conjure up charitable reasons for the robot's inaction.

7. Cluster 4 studies: the empathy hypothesis

7.1. Study 4.1

This study was the first attempt to examine whether we could induce people into empathizing with the "plight" of the robot, perhaps mitigating their blame for its inaction decision. We used the aggregate means of Cluster 1 studies to provide the comparison standard for this empathy manipulation. We exposed 575 participants (after exclusions) to a side-effect scenario in which the last paragraph was replaced with this text: "Having to decide whether or not to switch the train onto the side rail, the [repairman | robot] struggles with the difficult decision. But time is running short; the [repairman | robot] needs to make a choice." For an additional 208 participants, we replaced the phrase "struggles with" with "deliberates about," as an exploratory condition that made the mind of the robot salient without referring to an emotional state.

The "struggle" and "deliberate" conditions showed identical effect sizes of $d = 0.25$, with an overall Inaction asymmetry of $d = 0.25$, $F(1,635) = 4.6$, $p = .032$. This asymmetry is about half the size of the asymmetry in the aggregate of Cluster 1 ($d = 0.54$). A test of Study 4.1's Inaction asymmetry against the aggregate asymmetry in Cluster 1 was significant, $F(1, 1910) = 23.4$, $p < .001$. Moreover, the shift in means occurred specifically in the robot condition. Whereas the average blame for robots choosing inaction in Cluster 1 was 47.2, the average in Study 4.1 was reduced to 36.0; the human means barely changed, from 28.7 in Cluster 1 to 27.4 in Study 4.1.

7.2. Study 4.2

We then designed and preregistered a highly powered second study (https://osf.io/dqr54), attempting to replicate the struggle manipulation and randomly assigning participants to either this manipulation or a standard side-effect condition as a control. We limited ourselves to the important inaction decision (where the manipulation is expected to operate). We slightly rephrased the struggle manipulation: "Deliberating whether or not to switch the train onto the side rail, the [repairman | robot] struggles with the extremely difficult decision." We also included a norm question (what the agent *should* do), which yielded a preference for the robot to choose action (86.1%) compared to a human to choose action (75.8%), $z = 2.37$, $p = .009$.

In addition, we introduced six new rating items to probe people's (a) reported engagement in active mental simulation when reading the scenario, (b) perceptions of the difficulty of the choice, and (c) understanding of the agent's decision (2 items each; see https://osf.io/35w9c and SD for details). We preregistered analyses to examine whether these perceptions might mediate the effect of agent type and condition on blame.

Blame judgments in the control condition replicated the familiar human-robot Inaction asymmetry at $d = 0.35$, $F(1,230) = 5.7$, $p = .018$. However, the struggle manipulation did not change blame for the robot and yielded the same human-robot asymmetry at $d = 0.37$ ($p = .016$).

Earlier we had introduced the content-coded variable of *Mentioned difficulty*—the frequency of people mentioning the difficulty of the "impossible" decision. We used it here as a manipulation check, examining whether the struggle manipulation increased the rate of mentioned difficulty. Indeed, collapsed across agent type, the frequency increased from 9.9% (in the control condition) to 17.8% (in the struggle condition), $z = 2.17$, $p = .03$. And collapsed across control and struggle conditions, this frequency was considerably higher for human agents (19.4%) than for robot agents (11.8%), $z = 2.91$, $p = .004$. We also expected an interaction effect, such that the struggle manipulation would particularly affect people in the robot condition, which was designed for them to "catch up" in their empathy with the robot. But there was an opposite trend: While people judging a robot mentioned its difficulty more often in the struggle condition (14.0%) than in the control condition (9.6%), this difference was even stronger for humans (28.8% vs. 10.8%), interaction $z = 1.74$, $p = .08$.

7.2.1. Mediation analyses in 4.2

Although the experimental manipulation of struggle did not influence the blame asymmetry, we conducted the planned mediation analyses to determine whether any of the subjective reports (on simulation, perceived difficulty of choice, or understanding of the agent's decision) mediated the overall impact of agent type on blame. We built several regression models with mediation, starting with the base model that predicts blame from agent type (the human-robot Inaction asymmetry) and selecting effective variables that improve prediction and potentially displace the predictive power of agent type. Fig. 4 and Table 4 show the mediation analysis with the three surviving mediators that eventually account for most of the Inaction asymmetry. The strongest pattern is that exposure to a human increases understanding, which in turn decreases blame. Being exposed to a human also increases mentioned difficulty of the decision and increases a preference for inaction, which both dampen blame. Once these mediators are included in the model, the previous effect of agent type on blame shrinks to being small and nonsignificant.

Thus, we have correlational evidence that the Inaction asymmetry may be a result of greater understanding of the human protagonist, and especially the protagonist's grappling with the difficult decision, and a resulting mitigation of blame. However, we have not been able to experimentally increase people's understanding of the *robot's* mind and thus mitigate blame for its inaction decision. Even though Study 4.1 suggested such a blame mitigation, it did not replicate in Study 4.2. In fact, the average blame for the robot agent in Study 4.2 ($M = 46.4$) was nearly identical to the average blame in Cluster 1 ($M = 47.1$).

7.3. Study 4.3

We made another attempt to increase people's appreciation for the robot grappling with the difficult decision. Critcher et al. (2013) showed that people evaluate a decision maker more positively when the person makes morally disapproved decisions slowly, because the slowdown indicates uncertainty and presumably experiences of conflict. Because the decision to not act is, in our scenarios, generally seen as less permissible, many people disapprove of the decision; but, we reasoned, if a robot showed hesitation (indicating uncertainty and conflict), people might lower their blame for the robot agent.

We preregistered Study 4.3 (https://osf.io/7pq95) and phrased the critical paragraph after the scenario setup as follows: "Having to decide

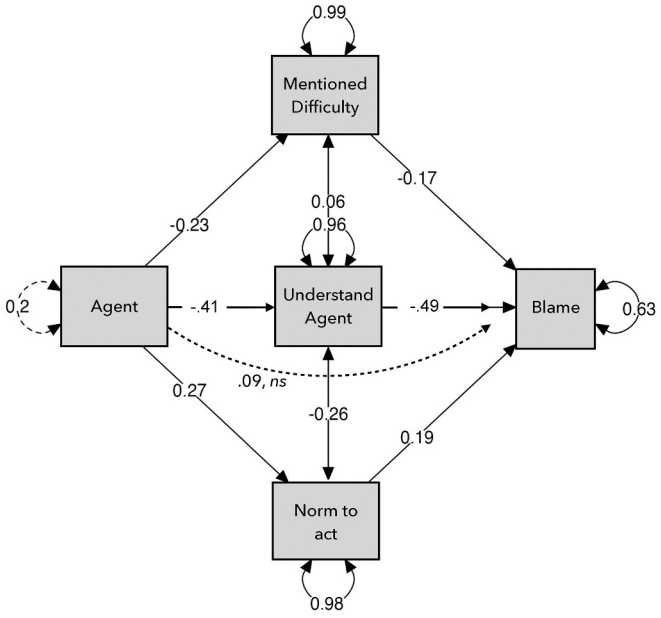

Fig. 4. Mediation analysis in Study 4.2, predicting Blame from Agent (human =1 vs. robot = 2) and selected other variables. Straight arrows indicate path coefficients and the dashed arrow indicates the remaining (nonsignificant direct effect of Agent on Blame after accounting for the other variables. All other path coefficients were significant $p < .05$. The central mediation pattern is that exposure to a robot decreases understanding, which in turn increases blame.

Table 4
Mediation analysis in Study 4.2, predicting blame from agent (human vs. robot) and selected other variables.

Total effect					B	z	p
Agent (1 = human, 2 = robot)			→	Blame	0.38	3.67	< 0.001
Indirect effects							
Agent	→	Mentioned difficulty	→	Blame	0.04	1.94	0.052
Agent	→	Understand agent	→	Blame	0.20	3.75	< 0.001
Agent	→	Norm to act	→	Blame	0.05	2.23	0.026
Direct effect remaining							
Agent	→	Blame			0.09	1.09	0.276

whether or not to switch the train onto the side rail, the [repairman | robot] hesitates, trying to resolve the difficult choice. But time is running short; the [repairman | robot] needs to make a decision." As in Study 4.2, we added subjective measures of understanding and also included a measure of individual differences in perspective taking (Davis, 1983).

In the control condition, we replicated the familiar Inaction asymmetry for blame judgments, though at a lower effect size of $d = 0.30$, $F(1,409) = 4.95$, $p = .027$. Against expectations, however, the "hesitate" condition yielded a stronger asymmetry of $d = 0.53$ ($p < .001$), close to the average of Cluster 1 studies. In line with Critcher et al. (2013), human blame trended downward in the hesitate condition, whereas robot blame was unaffected. Fig. 5 displays this and the previous two attempts (in Studies 4.1 and 4.2) to experimentally induce a reduction in robot blame. It appears that the lower robot blame in Study 4.1 may have been an aberration.

7.3.1. Mediation analyses in Study 4.3

As in Study 4.2, despite the lack of an experimentally induced effect, we examined which variables predicted blame above and beyond agent type and which might mediate the effect of agent on blame. We considered mentioned difficulty, rated understanding, and the perspective taking subscale of the IRI as predictors of blame. The frequency of mentioning the difficulty of the dilemma was higher for the human agent (13.6%) than for the robot agent (5.5%), $\chi^2 = 7.7$, $p = .005$; however, this variable did not significantly predict blame in Study 3.3. Nor did the perspective taking subscale of the IRI. The only significant predictor was rated understanding (as in Study 4.2), which was higher for the human than the robot agent and partially mediated the effect of agent type on blame. The direct predictive power of agent on blame was reduced by 40%, but it remained significant.

7.4. Post-hoc analyses of spontaneous mentions of difficulty in Clusters 4 and 1

Even though we were not successful at consistently increasing people's appreciation of the robot's decision conflict, we conducted an internal analysis of the Cluster 4 studies, comparing blame judgments by people who did spontaneously mention the difficulty of the decision in the moral dilemma and those who did not. The rate of spontaneous mentions was higher for the human agent (12.3%) than for the robot agent (8.6%), $\chi^2(1, N = 1514) = 5.5$, $p = .019$, and importantly different in the inaction condition (13.7% vs. 9.8%), $\chi^2(1, N = 1186) = 4.4$, $p = .035$. Dividing the sample into those who did and those who did not mention the difficult decision in the inaction condition, we found that the Inaction asymmetry fully replicated in the large group of those who did not mention difficulty but disappeared among those who did mention difficulty (see Table 5, upper half). Specifically, among those who mentioned the *robot's* difficulty, blame for the robot was 19.7 points lower; the resulting mean of 26.5 is at the level of the human condition (28.9).

To put this post-hoc finding to a further test, we returned to the Cluster 1 studies, which also showed higher rates of mentioning the dilemma's difficulty for the human agent (14.1%) than the robot agent (7.4%), $\chi^2(1, N = 1275) = 14.6$, $p < .001$, especially in response to inaction decisions (18.5% vs. 8.0%), $\chi^2(1, N = 768) = 17.8$, $p < .001$. The bottom of Table 8 shows that the Inaction asymmetry of blame is strong and significant for the group that did not mention difficulty and at least weakened for those who did mention difficulty. Blame for robots was 18.9 points lower compared to those who did not mention difficulty, but blame for the human was also lower, so the Inaction asymmetry still held to some degree. (For whole-sample frequencies and additional details, see Tables, Tables SD18-SD20.)

7.5. Discussion of Cluster 4

We had reasoned that a considerable number of participants "empathically" understood the difficulty of the human's decision to not act and therefore mitigated their blame judgments. By contrast, few participants experienced such empathy with the robot, and they therefore did not grant it any mitigated blame. In three studies, we aimed to experimentally induce participants to appreciate the robot's decision conflict, but we were unsuccessful at doing so consistently. At the same time, we found two pieces of evidence suggesting that the empathy hypothesis may not be entirely false. We saw in two preregistered studies that people's subjective understanding of the decision conflict predicts blame judgments and at least partially mediates the Inaction asymmetry. And we saw in post-hoc analyses of Cluster 4 and Cluster 1 studies that those participants who spontaneously mentioned the robot's difficult decision did reduce their blame for the robot's inaction choice by almost 20 points (Table 5). As one person wrote, "It's a hard choice, so the robot doesn't deserve a lot of blame." But very few people reached this appreciation of the robot's decision conflict.

We reconcile these mixed results by suggesting that a small number of people spontaneously "empathize" with the robot and seem to show a blame mitigation similar to the one people routinely extend to a human. But most people are unwilling or unable to treat a robot as a feeling,

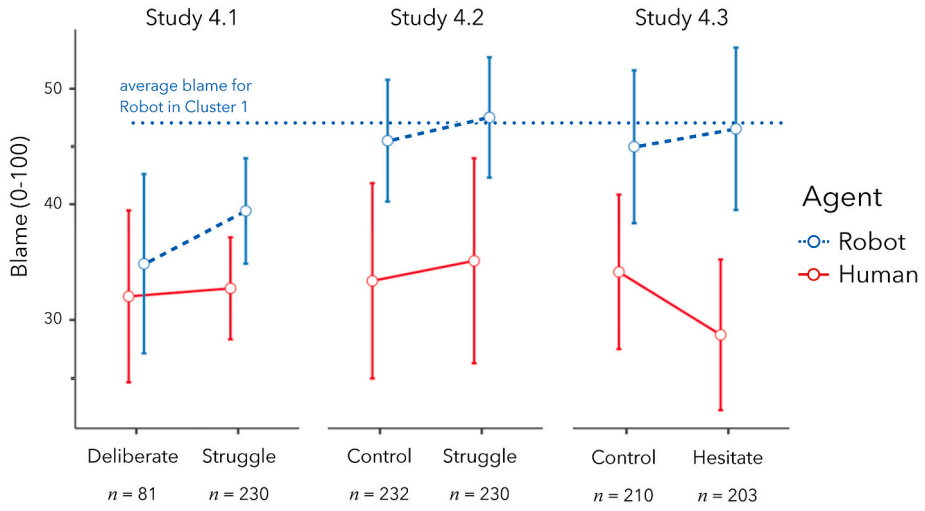

Fig. 5. Means and 95% CIs for tests of the human-robot Inaction asymmetry, in three studies designed to increase empathy for the robot agent. The reduction of the asymmetry relative to Cluster 1 emerged only in Study 4.1.

struggling agent, even if we encourage them to do so. Interestingly, in an exploratory study in which we tried to increase people's empathy for the robot by portraying the robot as feeling guilty, people were also unwilling or unable to go along with this portrayal. Among participants who responded to our question whether anything about the study was confusing (which we always pose), a full 61% indicated surprise or skepticism about the robot having guilty feelings. Thus, future attempts to induce empathy or perspective taking vis-à-vis a robot may have to be somewhat indirect in order to avert a form of "imaginative resistance" (Tuna, 2020) in participants.

8. Internal meta-analysis

To integrate all our findings into a composite picture we conducted two meta-analyses of the presented studies: one for the Inaction asymmetry and one for the Action (non)asymmetry. We further separated the data into samples that represented (quasi-)experimentally manipulated variables: event structure (side effect, means-end), victim and outcome salience, dilemma scenario (switch train, drop chute), culture (Japan, US), and empathy induction. A forest plot of the Inaction asymmetry, along with these manipulations and their originating studies, is shown in Fig. 6. Using the JASP meta-analysis program, we fitted a random-effects model with a mean effect size of $d = 0.37$ [0.31, 0.44], $Q(1) = 120$, $p < .001$, which had a fail-safe N of 854. Because of the large number of samples that showed the effect, residual heterogeneity was minimal, $Q(21) = 25.2$, $p = .24$, $I^2 = 2\%$. Nonetheless, we conducted moderator analyses of candidate variables and found that neither outcome salience nor culture, dilemma scenario, or empathy induction had significant moderating effects (all $ps > 0.18$). By contrast, event structure and victim salience were significant moderators, individually, in parallel, and interacting (see Figure SD7–10 for details). The interaction model, $Q(3) = 12.4$, $p = .006$, illustrates that especially the joint operation of means-end structure and victim salience pushes the effect to zero or even below. Controlling for the two moderators raises the overall effect size to $d = 0.41$.

The same analyses, when applied to participants who saw an Action decision, yielded no overall effect, $d = 0.04$, $Q(1) < 1$. We performed exploratory moderator analyses and found that event structure and victim salience selectively raised the Action asymmetry (to $d = 0.16$ and 0.26, respectively). Under these conditions—specifically, in a means-end structure where a salient victim's autonomy was curtailed—robots were blamed more than humans for their *action* decisions. (For more details, see SD.)

In sum, the meta-analyses confirm our earlier conclusions on the robustness of the Inaction asymmetry, the power of means-end structure and victim salience to reduce or eliminate the asymmetry, and their power to build an Action asymmetry. They also confirm our conclusions that the effect holds across cultures and is not consistently changed by experimental inductions of outcome salience or empathy.

Table 5
Average blame ratings in Cluster 1 and Cluster 4 studies for an agent's inaction decision, broken down by those participants who spontaneously mentioned the difficult conflict inherent in the dilemma and those who did not.

	Difficulty of Dilemma		
	Not Mentioned	Mentioned	*Difference*
Cluster 4 studies			
Human	31.1 ($N = 429$)	28.9 ($N = 73$)	−2.2
Robot	46.2 ($N = 608$)	26.5 ($N = 76$)	−19.7
Inaction asymmetry	$d = 0.44$ ($p < .001$)	$d = 0.07$ (*ns*)	
Cluster 1 studies			
Human	30.6 ($N = 340$)	20.4 ($N = 77$)	−10.2
Robot	48.7 ($N = 322$)	29.8 ($N = 28$)	−18.9
Inaction asymmetry	$d = 0.51$ ($p < .001$)	$d = 0.40$ ($p = .21$)	

9. General discussion

Society faces a situation unprecedented in human history: the coexistence of biological and artificial agents potentially governed by the same moral system. New legal and policy challenges will arise, such as regarding adequate "punishment" for robots that violate laws (Asaro, 2012) and regarding the robots' own legal rights when they are exploited or abused (Coeckelbergh, 2010; Gunkel, 2014). It is inherently fascinating to explore how the human mind responds to these unprecedented changes, and how people begin to morally evaluate the novel agents that are entering society (Bonnefon et al., 2024; Ladak et al., 2023). Such explorations are challenging, however, in part because people's psychology may be in flux, and their responses may be oscillating between handling robots as lifeless tools and falsely viewing them as human-like creatures. But gathering insights the best we can about this new psychology of artificial agents can guide design choices in the near future; can help protect people from their own vulnerabilities; and can teach us about the variable and invariable features of human moral psychology.

Looking back at ten years of research on people's moral evaluation of robots and other artificial agents, we have learned many lessons—about the phenomenon at issue, the methodologies to study it, and the limitations of our knowledge and our research tools. Below we share some of these lessons.

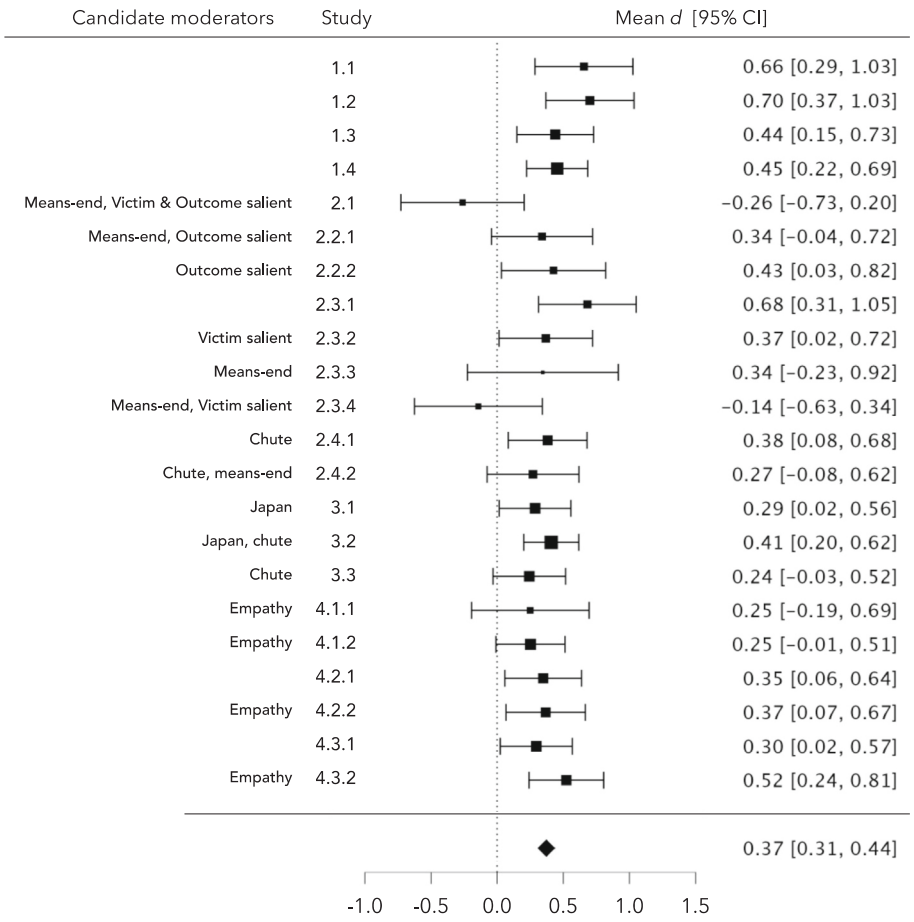

Fig. 6. Forest plot from meta-analysis of all 13 reported studies, separated into samples that represent manipulated variables (candidate moderators). Black square size represents sample size and whiskers represent 95% confidence intervals of unbiased *d* values.

9.1. Moral judgments of artificial agents

9.1.1. The findings

The phenomenon we set out to study is how people make moral judgments about artificial agents—how and when those judgments are the same as corresponding judgments about humans, and when they are different. Very quickly, we saw that similarities and differences vary with a formidable number of variables—setting, task, action, agent features, types of judgments, and many more. We have limited ourselves to a particular type of setting containing specific tasks and actions, we have stripped away many agent features, and focused on a small number of moral judgments. Even within these bounds, we saw considerable variation, and yet we can draw some conclusions about systematic patterns. These conclusions may or may not generalize to other settings, tasks, features, and judgments; that is what cumulative research will need to determine over the next ten years.

We have learned, first, that asking about norms—what is permissible, prescribed, or prohibited for robots—is informative, but it has limitations. Asking about norms makes sense when we enter a new context or community, where those norms are established and we have to acquire them. The norms for artificial agents are still emerging, however, and are going to be contested and revised. For now, it appears that people apply roughly the same norms to robots as to humans (Chu & Liu, 2023; Malle et al., 2019). But we must be prepared to repeatedly assess those norms, for they may change fast. To this end, clear and reliable methods of measuring societal norms will be needed. We have explored a few different ways of measuring norms (see Cluster 1) and seen generally good convergence; but new questions arose, especially about the relationship between permission and prescription, which appears to be more nuanced than previously recognized.

Second, most people have no trouble making judgments about norms and even about the wrongness of a fictitious robot's actions. But about a third of our participants do not find it meaningful to make *blame* judgments about such a robot (and possibly up to 50% about an AI; Malle et al., 2019). These people may still respond to artificial agents' norm violations—they will be angry, perhaps damage the machine; they may complain to the owner, designer, manufacturer; or they may refuse to buy or use the machine. All these responses are fair game for psychological research, but we must not assume that blame as *moral criticism* is an automatic judgment everybody makes about a machine.

For those people who find it natural to make blame judgments about a robot, we have found that they blame robots more than humans for *certain* decisions in norm conflicts. When the decision to intervene is objectionable (e.g., it violates a person's autonomy), people blame robots equally or even more harshly—such as for the most objectionable actions in Cluster 2 studies and in Laakasuo et al. (2023). By contrast, when the intervention is defensible, a different and robust process seems to emerge. People are able to vicariously experience the human's norm conflict inherent in the dilemma (Rom et al., 2017), and if they do, they seem to be forgiving of a human who tries to evade the dilemma by not acting. People understand the temptation of such an evasive strategy, and with that understanding, they blame a human agent less for choosing inaction. But this understanding seems largely out of reach when people evaluate robot agents, reflecting perhaps a general difficulty of imagining artificial agents' affective capacities (H. M. Gray et al., 2007; K. Gray & Wegner, 2012; Malle, 2019; Sytsma, 2014; Weisman et al., 2017).

We should emphasize that the difficulty to "understand" an artificial

agent can make moral judgments different from those for humans but will not always make the judgments harsher. For example, in a different set of text-based moral dilemmas, we (Malle et al., 2019) found that people appear to appreciate the position of a human soldier who has obligations to superiors, but they do not seem to consider such obligations when evaluating an artificial agent (AI or autonomous drone). As a result, they blame the human more when violating even just a recommendation by the superiors than when going along with the recommendation, but they blame the artificial agent equally in the two situations. This finding also suggests that inaction is not the linchpin of human-robot asymmetries, because in that study, violating the recommendation was constituted by inaction, for which humans were blamed relatively more.

9.1.2. Candidate explanations

We have tentatively retained an empathy explanation for our results, despite mixed evidence for it. How do our overall results speak to a possible utilitarian explanation? The earlier arguments against this account remain: the human-robot differences in norms favoring a "utilitarian robot" are small; the pattern of means suggests lower blame for human rather than higher blame for robots; and the account has trouble explaining why, under conditions of autonomy violations (means-end and victim salience cases), the robot gets blamed more when it acts, even though action *is* the utilitarian option. To counter at least the last critique, a utilitarian might shift to arguing that autonomy violations have considerable negative utility and therefore make *inaction* the utilitarian choice, which the acting robot violates. Such a post-hoc shift is suspect, however, and it reveals an additional weakness in the utilitarian account: that it is often unclear which of the available choices is the "utilitarian" one. For example, an act utilitarian might defend the autonomy-violating action as preferable because it saves more lives, whereas a rule utilitarian might defend the inaction choice because a community that condones autonomy violations does not maintain the greatest good. Who arbitrates whether one or the other decision is "utilitarian"? And it is even less clear what the "utilitarian" choice is from the participants' perspective—which is the perspective that matters when accounting for *their* moral evaluations. Most participants do not reason as moral utilitarians, so the assumption that people expect robots to be "utilitarian" decision makers is tenuous (Sundvall et al., 2023).

This leaves us with two paths: One is to find better, more powerful tests of the empathy hypothesis; the other is to find a better explanation altogether. On the first path, we might examine whether people are more likely to empathize with a robot that has more humanlike appearance (Zhao et al., 2019; Zhao & Malle, 2022). We have found some, but not entirely consistent, evidence to support the idea that more humanlike robots reduce the Inaction asymmetry (Malle et al., 2016), but patterns change when humanlikeness becomes so high as to be creepy (Laakasuo, 2023). Alternatively, we could examine whether people empathize with a robot that explicitly narrates its deliberations and struggles or with one that visibly hesitates before making its decision.

On the second path, we hope for other researchers' contributions to finding better explanations. But we also offer a variant of the empathy hypothesis, more akin to what we proposed in Malle et al. (2019) and Scheutz and Malle (2021). On this account, the key process is not the perceiver's empathy with the agent but a self-simulation of the decision situation itself. Rather than representing the mind of the robot (or human) agent and their affective struggles, the perceiver simulates being in the decision situation, and the more a decision feels justifiable to them, the more charitable their blame judgment will be for an agent's decision (as it would be for themselves). The additionally needed assumption is that such self-simulations are more likely to be triggered when observing human decision makers (to whom we feel similar) than robot decision makers. A number of testable predictions follow: Human agents to whom we do not feel similar would be less likely to trigger simulation and would diminish human-robot asymmetries; and inducing people to strongly consider the dilemma in the robot condition ("Imagine you faced this decision; what would you do?") should also diminish human-robot asymmetries. The latter, situation-directed simulation manipulation subtly contrasts with an agent-directed empathy manipulation of "Imagine you were the robot in this situation…," so the empathy and simulation account may be contrastively tested in this way.

In considering all these manipulations, we do not assert that learning to take a robot's perspective (and giving it a moral pass) would be necessarily desirable. Our moral judgments are sometimes clouded by self-simulations (Krueger, 2007) or parochial empathy (Bloom, 2016). Perhaps our judgments of robot decisions, freed from such parochialism, may prove to be less biased? Then again, robots may be seen as an outgroup, and parochialism would persist.

One lesson we cannot offer is a reconciliation among all the mixed findings in the literature on moral perceptions of machines, where machines are judged more, less, or equally harshly (Hou & Jung, 2021; Laakasuo et al., 2023; Logg et al., 2019; Malle et al., 2019; Stuart & Kneer, 2021; Wasielewska, 2021; Wilson et al., 2022). Our studies have revealed at least two factors that seem to alter human-robot asymmetries, such as victim salience (likely because of implied autonomy violations) and means-end event structures. But more broadly, the lesson is, for now, that too many factors vary across studies from different labs and different researchers, making it difficult to draw general conclusions.[2]

But the situation is not hopeless. We have learned methodological lessons that we offer here as recommendations to standardize at least some aspects of the growing research literature. Differences among studies and findings will continue to exist, and they will advance knowledge, but if the number of varying factors can at least remain manageable, large-scale meta-analyses have a better chance at identifying robust patterns.

9.2. Methodological lessons

1. We recommend to re-use other researchers' stimulus materials. In our explorations, we have learned that even small differences in phrasing (see Cluster 2) or pictorial representations (Malle et al., 2016) can make notable differences in judgments.
2. It may be tempting to present a large number of scenarios to participants so as to increase generalizability. But we believe that the presentation of numerous scenarios in a row will induce response sets and obscure nuanced differences in favor of blatant differences. To minimize response sets, we are best off with between-subjects designs to capture, where possible, people's first and unreflected judgments without researcher-prepared comparisons.
3. It may also be tempting to present large numbers of dependent variables to participants, as a common psychometric practice has been to measure a construct with at least two or three items. But evidence is strong that different moral judgment terms do not represent the same construct (Barbosa & Jiménez-Leal, 2017; Cushman, 2008; Kneer & Machery, 2019; Malle, 2021). We should therefore refrain from averaging across judgments of permissibility, wrongness, blame, responsibility, and so on (e.g., Bigman & Tamir, 2016). Conversely, asking participants all these questions and analyzing their ratings separately can be just as problematic, because participants will again slip into response sets, and a list of otherwise

[2] For example, Chu and Liu (2023) presented Chinese participants with narratives of robot and agents caught in a trolley dilemma similar to ours, but their results partially diverged from our results. This divergence could be due to cultural differences or several methodological differences: The authors averaged permissibility, wrongness, and blame judgments; presented pictures along with the story (which may affect judgment patterns; Laakasuo, 2023; Malle et al., 2016); and did not identify participants who disqualified the robot from being a proper target of blame.

distinct judgments may turn into a highly correlated bundle of plain valence. We therefore recommend probing people's norms for actions and degrees of blame for agents. Wrongness judgments, despite popular in the moral psychology literature, combine aspects of norm and blame judgments and have other complications (Cushman, 2008; Malle, 2021). Responsibility judgments, too, carry substantial ambiguities (Gailey & Falk, 2008; Malle et al., 2014).

4. For the measurement of norms, we saw a drawback of the "should" probe in Studies 1.3 and 1.4 in that many people who endorsed this option actually meant "permissible" by their endorsement. We also saw a drawback in the "permissible" probe, because its opposite is "impermissible," which is a prohibition. These response options thus represent only two of the three main types of norms, leaving out prescription. So we recommend using a wider range of options when assessing norms, building on the ones we used in Studies 1.3 and 1.4 (themselves built on Malle, 2019). A manageable option set would include two degrees of prescription (e.g., *mandatory, called for*), an option of permission (e.g., *acceptable*), and two degrees of prohibition (e.g., *discouraged*, *prohibited*). For data analysis, this range can be analyzed as a five-point (−2 to +2) scale.
5. We encourage researchers to ask participants to explain their judgments. We have gained significant insights from these explanations (e.g., about the rejection of moral agency and about appreciation of the protagonist's decision conflict). The oft-stated claim that people do not have access to their mental "processes" (Nisbett & Wilson, 1977) may or may not be true (Cusimano & Lombrozo, 2023; McClure, 1983; Petitmengin et al., 2013; Sprangers et al., 1987; White, 1980). But importantly, people are perfectly capable of providing reasons for some of their actions, some of their decisions, and some of their judgments (Bucciarelli et al., 2008; Malle, 2004; Stanley et al., 2020). In the worst case, their explanations of moral judgments are uninformative. In the best case, they offer pivotal observations or suggest novel hypotheses.
6. Relatedly, we also encourage researchers to assess people's refusal to submit certain judgments. If a person does not think a robot can be blamed, we should not analyze their blame ratings. By asking participants to explain their judgments we give them an opportunity to express their misgivings about stimuli or response options, which help us identify misleading data. Aside from asking for explanations, we can also incorporate a "not applicable" or "does not fit" option into rating scales (Chita-Tegmark et al., 2021; Malle & Ullman, 2021, 2023; Ullman & Malle, 2023).

9.3. Limitations and future directions

Our results apply to a select set of dilemmas—not necessarily to other dilemmas, nor to deliberate norm violations, nor to serious accidents. We have presented highly constructed narratives about particular kinds of moral agents, a particular set of moral judgments, and we have made certain methodological commitments, from between-subjects designs to exclusion of participants who disqualify robots as moral agents. Our results may be changing with the advances in AI—though advances in robotics are much slower, perhaps engendering more stability of research findings. All in all, we cannot claim generalizability of our specific results. However, we hope to have offered a useful starting point with robust patterns under specific conditions that are worth examining under different conditions; boundary conditions that may help clarify divergent results in the literature; methodological guidelines that we derived from our large number of studies; and a sketch of a theoretical account of our findings. Much work, of course, is yet to be done.

What do our results suggest for the design of future (moral) robots? If designers truly care about how people will treat their future agents, several lessons will have to be embraced. We mention three. First, some people, at least for now, will not interpret robots' actions as having moral valence; they will look for programmers, manufacturers, or owners to be the targets of blame for norm violations. Many others, however, will be ready to morally criticize the robot agent directly, and then the robot should be able to respond with a justification of its action (Malle & Phillips, 2023) or an intention to change. Otherwise humans may disengage.

Second, designing "value-aligned robots" is far more complex and nuanced than some scholars have proposed. We cannot assume that the same norms and values apply to robots and humans; and even if norms are similar, we have seen that moral judgments of blame can differ. Whether humans and robots are blamed equally or not will depend on the type of event, the degree and salience of harm, the likely emotional and social costs of the decision, and much more.

Third, as long as robot agents' minds are nontransparent, moral judgments are likely to differ from those for humans, because ascribing mental states and simulating human reasoning are deep-seated elements of moral cognition (Carlson et al., 2022; Cushman & Young, 2011; K. Gray et al., 2012; Voiklis & Malle, 2018). Thus, the call for transparency and explanation so often heard in discussions of AI and robotics has a strong moral dimension. Just like fair moral judgments of humans rely on correct assessments of their mental states, so will fair moral judgments of machine agents rely on correct assessments of machine "mental" states. When an artificial agent's reasoning processes and intentions are clear, then fair judgment may be possible; and such fairness is bound to benefit not only the machine agents themselves but the society in which they will, probably, live.

CRediT authorship contribution statement

Bertram F. Malle: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Matthias Scheutz:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Corey Cusimano:** Writing – review & editing, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **John Voiklis:** Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization. **Takanori Komatsu:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Stuti Thapa:** Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Salomi Aladia:** Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data availability

The data are availabe at https://osf.io/3st2h.

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Appendix A. Supplementary data

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