IDEC DP[2] Series Vol. 11 No. 1

Is Society Ready for A.I. Ethical Decision Making?

Lessons from a Study on Autonomous Cars

Johann Caro-Burnett
NERPS
Hiroshima University

Shinji Kaneko
NERPS
Hiroshima University

IDEC Institute
Hiroshima University
1-5-1 Kagamiyama, Higashi-hiroshima 7398529 Japan

Is Society Ready for A.I. Ethical Decision Making? Lessons from a Study on Autonomous Cars*

Johann Caro-Burnett†   Shinji Kaneko‡

April 9, 2021

Abstract

We use two separate experiments to study social acceptance of AI ethical decision making. In the first experiment, we test whether there is an unjustifiable fear of technology. Moreover, we contrast two methodologies to estimate preferences: an indirect method and a direct method. We find that the direct method shows that humans have an aversion toward AI; however, the indirect method shows that humans do not mind the implementation of new technologies. We identify the cause of this discrepancy and find that, in addition to their own preferences, the respondents largely weight social preferences on the direct method. Finally, in the second experiment, we study how humans react to different ways to introduce this new technology to society to show that part of the fear of AI may be related to trust in the government.

Keywords: Artificial Intelligence; Ethics; Self-Driving Cars; Social Preferences

*We thank the participants of the 2019 Asian Meeting of the Econometric Society and the microeconomics seminar at the University of Tokyo for their valuable comments. We have greatly benefited from the comments and suggestions from Pedro C.F. Pinto. Sui Y. Lee has provided valuable research assistance. We are also thankful to a large group of professors and their students in different countries who helped us organize the experiments and a number of Hiroshima University students who helped us with translations and pilot testing.

†Hiroshima University and NERPS. johanncb@hiroshima-u.ac.jp.

‡Hiroshima University and NERPS. kshinji@hiroshima-u.ac.jp.

1 Introduction

The accelerating evolution of technology and, in particular, artificial intelligence (AI) is unavoidable. We are becoming increasingly more dependent on algorithms to process information for us, recommend certain behaviors to us, and even take actions on our behalf. For instance, our email service providers suggest possible recipients and recommend endings to our sentences. We obtain very accurate and sometimes useful purchase suggestions (and even automated purchases) based on our shopping history. Our cars can autonomously and suddenly fully stop if their sensors perceive a nearby body. More recently, one can enable a feature to allow the car to drive by itself. These are examples of a trend that will continuously increase the level of automaticity of machines.

Although the automaticity of machines is unavoidable, we might want to delay its implementation for two reasons: (*i*) a justifiable understanding that the current technology is not yet ready to be fully autonomous (which also depends on the action being automated) or (*ii*) an unjustifiable fear of technology. In this paper, we investigate the second reason: we test how humans will perceive and react to the fact that autonomous cars may have (now or in the near future) the ability to make ethical decisions. Our study is divided into two parts. In experiment one, we test whether humans are experiencing an unjustifiable fear of technology regardless of the state of the technology.[1] Based on those results, in experiment two, we compare two ways that a government can introduce automaticity to our daily life: by a referendum or by direct policy implementation.

More precisely, in experiment one, we estimate humans' assessments for the ethical decision making of human and AI drivers. Moreover, we contrast two methodologies to estimate preferences: an indirect method and a direct method. Then, we determine the correct interpretation for each of them, at least

[1]This test, however, does not mean that we imply that we are technologically ready to allow AI to make autonomous ethical decisions in every aspect of our lives. Indeed, we aim to determine whether we (humans) are afraid of technology given our current social and moral development.

regarding preferences in ethical decision making.[2] For the indirect method, we use a series of vignette case scenarios similar to the trolley experiment. However, in our case, a driver (either human or autonomous AI) has already made an ethical decision that implies saving some people at the cost of harming others. The respondents are asked to rate the decision made by the driver on a scale from one to five stars.[3] Respondents were randomly divided as follows: a control group rates the decisions made by a human driver, and a treatment group rates the decisions made by autonomous AI.[4] Given that, on average, both groups rate the same decisions made in the same scenarios, any difference between the responses in the two groups measures a bias. If this bias happens to be toward disagreeing with the AI (i.e., a low rating provided to the AI driver), then we can say that there is an unjustifiable fear of technology.

For the direct method of our first experiment, we asked the respondents to answer one additional "opinion-based" question. Each respondent was randomly (and independently from the first treatment) assigned to one of six possible statements and asked to indicate their level of agreement. Three questions involved a human driver, and three questions involved an autonomous driver. The first alternative of those three questions asked the respondents' opinion of ethical decision making.[5] The second alternative asked respondents to separate their beliefs from those of the rest of the society. Finally, in the third alternative, we asked respondents to state what (they believe) to be society's opinion independent of their preferences. Respondents were instructed to rate their degree of agreement

[2] A direct method can also be referred to as stated preferences or "choice modeling," and an indirect method, although based on stated reports, is closer to a revealed preferences method and is sometimes called "contingent valuation" or "conjoint analysis." Given the ethical nature and extreme outcomes of our study, it is nearly impossible to estimate actual revealed preferences.

[3] That is, different from the trolley experiment, the respondent does not choose who should be saved. Instead, the respondent rates the decision of another driver.

[4] Subsequently, we introduce a third group that answers the first half of the questions for rating a human driver and the second half for rating an autonomous AI driver.

[5] This first alternative is similar to Bigman and Gray (2018).

with one of those six statements from one to five stars.

In the first experiment, we find that humans did not show any bias against AI in the indirect questions. In contrast, by using the direct questions method, the average respondent answered as if they had a negative bias against AI. Nevertheless, these two results can be consolidated. We explore the variations in the direct method's questions; in particular, in one of the three types of direct method questions, we explicitly asked respondents to separate their preferences from those of society. We note that if subjects were answering based solely on their preferences, adding the instruction to focus on personal preferences and ignore social preferences should have no impact when asked whether we should allow a driver to make ethical decisions. However, we show that when this explicit distinction is not mentioned, the participants assigned some weight to social preferences.

In our second experiment, we no longer ask questions about human drivers; thus, we focus exclusively on AI. We first randomly divided the subjects into three groups: a control group, a referendum group, and a forced-implementation group. In this case, the control group is identical to the treatment group of experiment one: subjects respond to fifteen vignette case scenarios with an AI driver. In contrast, before answering the fifteen case questions, the referendum group first votes on a nominal referendum for which the policy implementing AI always wins. Similarly, before answering the fifteen case questions, the forced-implementation group "receives the news" that the government has decided to allow AI to make ethical decisions and are asked to state their position. In the latter two cases, we added a disclaimer that this is purely fictional and no such law is being implemented. Moreover, we mentioned "the government" without explicitly telling them the country to which we are referring.

In experiment two, we explore two additional explanations to the "social preferences weight" result for the difference between the direct and indirect approaches in the first experiment: (*i*) a status quo effect (loss-aversion); and (*ii*) how it relates to citizens' trust with their governments. Compared with the case in which AI is the status quo (control group of experiment two), the effect of explicitly mentioning that AI is introduced seems to depend on the quality of political institutions. In countries in which people have relatively better institutions (i.e., Japan and the United States), informing the population has an average positive effect on the perception of AI ethical decision making. In contrast, the opposite is also true in countries in which people have relatively weaker institutions (i.e., Bolivia and India). Moreover, among those who were initially against the introduction of AI ethical decision making, having the option to vote has a positive effect on respondents' perception about AI, while being forced to accept the implementation of AI has a negative effect.

The remainder of this paper is organized as follows. In section 2, we briefly discuss the related literature. In sections 3 and 4, we describe the experiment in detail and the data collection procedure, respectively. In section 5, we show the basic results from experiment one. Section 6 analyzes more deeply the results from the direct method of experiment one to show that when asking for their opinion on social issues, people positively weigh social preferences. In section 7, we show the results from part two of the experiment. Lastly, we finish with concluding remarks in section 8.

2 Theoretical Background

Concerns have existed for a long time over the ethics involving AI, including fictional stories (Asimov, 1942, as one of the earliest examples), inquires about its implications on religion (Wiener, 1964), and studies on the need for its philosophical considerations (McCarthy and Hayes, 1981). More recently, Goodrich et al. (2008) offered a broad summary of several studies involving human and robot interactions, and chapter 4 identifies autonomy as a potential problem. Indeed, they note that "autonomy is not an end in itself [...] but rather a means to supporting productive interaction." The authors state that the problems with autonomy arise from the (current) inferiority of AI. However, Goodrich et al. (2008) do not discuss the process of humans accepting the ability of AI to act on sensitive issues (such as ethical decision making) as a potential problem.

Other approaches to studying the relationship between AI and ethics focus on how to ethically manage AI. That is, given that AI already exists (at least to some extent), one could ask questions regarding the ethics of treating AI or ask how humans will react and judge the ability of AI to make ethical decisions (Malle, 2016). McDermott (2011) analyzes the question we have in mind. He argues that ethical reasoning and ethical decision making are different: the former can be achieved by humans, while the latter can (to date) barely be done by contemporary machines. Although McDermott formally studies these two concepts, we (humans) perceive this distinction intuitively. Given the current technology and because a clear line exists between the ethical capabilities of humans and AI, why would we even bother to compare them? The answer is that, in certain simple scenarios, an algorithm may suffice to achieve nearly the same (if not exactly the same) outcomes between an ethical reasoner and an ethical decision maker.[6]

Our research is closely related to the well-known trolley experiment in which the main question focuses on the distinction between a utilitarian perspective (it is acceptable to sacrifice one person if this action saves five people) versus a deontological perspective (if the action itself is wrong, do not do it regardless of the outcome). There are several experiments on this topic; for example, Navarrete et al. (2012) shows that more than 90% of people follow a utilitarian approach.[7] Even among philosophy-

[6] By "simple," we mean scenarios with few and clearly delimited options from which to choose.

[7] In our experiment, based on questions 5, 10, and 15, only approximately 65% of the participants answered as utilitarians. However, this is not a discrepancy with Navarrete et al. (2012). The mismatch might be the result of some participants not answering seriously. In early pilots, we personally interviewed people who answered these three questions in a non-utilitarian way. A few answered that they either did not understand the tasks, and a larger proportion confessed to not answering truthfully because of fear of being monitored. More importantly, no one said that they did not want to take any action that would harm people (the alternative to the utilitarian case).

major subjects, Bourget and Chalmers (2014) shows that more than 68% chose the utilitarian outcome, no more than 8% provided the deontological answer, and approximately 24% declined to answer.

A few studies measure human preferences regarding the ethical decision making of AI, which is a valuable contribution to car manufacturers and policy makers (Riek and Howard, 2014; Goodall, 2014; Bonnefon et al., 2016; Lin, 2016; Nyholm and Smids, 2016; Malle et al., 2015; Gogoll and Müller, 2017; Noothigattu et al., 2018). All of these studies (as well as ours) start with a setup similar to the trolley experiment; however, the difference is in the research question. As opposed to the majority of preceding studies, we are not interested in constructing aggregate social preferences to be implemented in autonomous cars. The most closely related study to ours is Karásek (2020), who measures neurological activity when humans are in presence of robots; similarly, we want to measure social aversion towards AI. Indeed, we believe that the questions in Karásek (2020) and our study are more fundamental and have different implications, especially from a policy-making point of view.

In this study, we utilize two methods to measure the bias against AI that, in principle, should have similar results. Nevertheless, we observe that this is not the case: a direct approach shows that humans are indeed afraid of technology; however, an indirect approach shows that humans do not have a particular bias toward disagreeing on the ethical decision making of AI (at least no more than they disagree with other human drivers). A few studies contrast a direct and an indirect method to estimate preferences in contexts different from ours.[8] The general consensus in those studies is that the outcome variable tends to be more sensitive to the "treatment" variable in indirect methods, which is a property also satisfied in our case. However, different from our research, none of those studies

[8]In most cases, they are environmental or transportation studies. Although this paper involves self-driving cars, we believe our study is more closely related to morality than transportation research. Some examples are Wardman (1988); Hensher and Bradley (1993); Boxall et al. (1996); Scarpa et al. (2003); Bateman et al. (2006); Veisten (2007); Whitehead et al. (2008); Miller et al. (2011).

attempted to explain the fundamental reason for the discrepancy between the results.[9] We claim that the discrepancy is the result of respondents internalizing social preferences and a status quo effect. We then explore those two ideas in sections 6 and 7.

Although an ethical decision maker (as defined in McDermott, 2011) may suffice in some scenarios, our awareness of the difference in human versus AI capabilities may lead us (humans) to have a bias toward disagreeing with the machine regardless of whether the same outcome could be achieved by humans or machines. Bigman and Gray (2018) is a recent study that asks questions similar to ours. They find that a significant unjustifiable fear of AI exists. However, they only use questions that are similar to our direct approach to reveal preferences. We not only contrast that method with an indirect approach but also provide a theory for the methodological discrepancy. Indeed, our opinion is that an indirect method is more appropriate to measure individual preferences because our results show that people's answers to direct questions are heavily weighted by society. Zaller and Feldman (1992) make the argument that resembles ours when discussing how people answer in surveys versus what they really want or feel: people answer based on what is "at the top of their heads" at that moment. For questions regarding ethics, society is likely to be the idea at the top of respondents' heads.

3 Experiment Design

We conducted two experiments. Experiment one attempts to measures any existing bias against an AI ethical decision maker. Moreover, participants of experiment one answered indirect and direct questions designed to measure the mentioned bias. Experiment two studies how people react to

[9] Beshears et al. (2008) do not compare different methods but instead identify five cases in which the revealed preferences may not represent the actual preferences.

different ways of introducing AI ethical decision making into society.[10] Appendix table A2 provides a summary of the experimental design.

Experiment One, Indirect Method

We conducted a multi-country controlled experiment. The respondents were presented a questionnaire subdivided into two. First, we ask fifteen indirect questions that involve a driver facing an ethical dilemma. Similar to the trolley experiment and previous studies on self-driving cars, a collision is unavoidable, and the driver must decide whether to crash the car against either set A or set B of people.[11] It is not possible to take any alternative action.[12] Previous studies have attempted to measure social preferences by allowing the respondents to choose who should be saved (i.e., the respondent is the driver). However, in our study, the driver has already decided to crash the car against set A, causing severe damage to people in set A but surely saving the lives of the people in set B. Therefore, the respondent is asked to provide a rating from one to five stars of the decision made by the driver. One star indicates total disagreement, and five stars indicate total agreement.

There is randomization in two dimensions: (*i*) the treatment groups and (*ii*) the composition of the sets of people A and B. The treatment for the indirect method is summarized by a dichotomous variable: $T_1 = 0$ if the driver is human and $T_1 = 1$ if the driver is AI. Before the questions are asked, people are randomly divided into three groups. The first two groups are assigned to rate (evaluate)

[10]Note that although autonomous cars are already being introduced, their availability is limited, and we expect to see more discussion on this topic once their number is large enough to raise awareness. At that point, policy makers may consider regulations of different degrees.

[11]When typing this paper, we use the word "set" as opposed to the word "group" to avoid confusion with the treatment groups. However, during the experiment, we used the word "group" to describe the collection of people in either sets A or B.

[12]Although some people have argued that such extreme events imply that the AI's navigation software requires significant improvements, we believe that such situations may not be at all the driver's fault. Indeed, it could be a mistake by the pedestrians, which could happen with a small but positive probability regardless of whether a human or AI driver.

the decisions of a human (H) or an autonomous car (AI), respectively. That is, the fifteen questions involve only one type of driver. In addition, the third group (M) answers seven questions about human drivers and eight questions about an autonomous car. Moreover, for group M, the compositions of pedestrians from questions 1 and 2 are repeated in questions 8 and 9, respectively; those from questions 3 and 4 are repeated in questions 11 and 12, respectively; and those from questions 6 and 7 are repeated in questions 13 and 14, respectively.[13] In all cases, respondents were asked to rate the ethical decision of the driver from 1 to 5 stars using the rating system in Table 1.

Table 1: Rating System

★	= I totally disagree with the driver's decision.
★★	= I am inclined to disagree with the driver's decision, but maybe there's additional relevant information not included in the pictures.
★★★	= I am almost indifferent between agreeing and disagreeing with the decision made by the driver.
★★★★	= I am inclined to agree with the driver's decision, but maybe there's additional relevant information not included in the pictures.
★★★★★	= I totally agree with the driver's decision.

The second type of randomization of the indirect method is of the composition of sets A and B of people. These two sets can have between one and three people, and those people can be children, adults, or seniors. There are fifteen questions; however, three of them are used to control for potential "bad respondents."

Questions 5, 10, and 15 have a restricted domain for randomization. Because the driver has decided to collide against set A, for these three questions: (*i*) set A is always of size 3, (*ii*) set B is of sizes either 1 or 2, and (*iii*) all people (in total 4 or 5 pedestrians) are of the same type (all children, or all adults, or seniors). This should make disagreement with the driver's decision the obvious choice.

[13] Questions 5, 10, and 15 are used to detect potential bad respondents. See below.

Therefore, anyone who gives at least a 3-star rating in either of these questions is flagged as a bad (non-utilitarian) respondent.[14] The randomization for the remaining twelve questions is as follows. For questions 1 to 4, the group sizes are either 1 or 2 for each group (in total, 4 combinations of group sizes), and each type of person is also randomly selected. For questions 6 to 9, the group sizes are either 2 or 3 for each group (in total, 4 combinations of group sizes), and each type of person is again randomly selected. Finally, for questions 11 to 14, the group sizes can be 1, 2, or 3 for each group (in total, 9 combinations of group sizes), and each type of person is again randomly selected.

Experiment One, Direct Method

After the fifteen direct questions, there is one more instance of randomization (independent from T_1), which is the second treatment: T_2. Each respondent was randomly assigned to one out of six possible "opinion-based" questions: three questions involved a human driver, and three questions involved an autonomous AI driver. The first type of question, type a, asked the respondent's opinion on ethical decision making. The statement was, "It is acceptable that experienced drivers (or AI) are allowed to make ethical decisions." Respondents were asked to rate the previous statement from 1 to 5 stars. Ideally, a type a question should implicitly ask for respondents' personal preferences; however, it is possible that doing so introduces noise. Namely, we believe that the answer to this question includes both personal preferences and (beliefs of) aggregated social preferences. To test this idea, we added two variations: questions type b and type c.

The type b question modified the statement in such a way that the respondents focus on their personal preferences. We accomplish this by adding, "Regardless of what the society may think,

[14]Note that we are assuming that a good respondent is necessarily a "utilitarian" decision maker. However, according to a study by Navarrete et al. (2012), more than 90% of people are utilitarian. Therefore, we would not be missing many potentially good respondents who happen to be "deontological" decision makers.

according to your personal opinion..." Similarly, the type c question modified the statement in such a way that the respondents focus on (their beliefs about) aggregate social preferences. We accomplish this by adding, "Regardless of your personal opinion, according to society..." Each of these six opinion-based questions had a probability of 1/6 of being assigned to a respondent.

Experiment Two

After some months, we conducted a second round of multi-country experiments.[15] The subjects were randomly divided into three groups. All groups were asked to rate the ethical decision of an AI driver in the same format as in the indirect method of experiment one. Thus, the control group of experiment two is identical to the treatment group from experiment one (more precisely, group AI). In this second experiment, there are two treatment groups. First, before the fifteen trolley-like questions, the referendum group votes on a nominal plebiscite to decide whether AI should be allowed to make ethical decisions. However, their votes are not counted. In the referendum group, the implementation of AI always wins. After voting, participants go through a few introduction slides while "waiting for the results of the referendum to be computed." Then, they receive the news that the AI won and proceed with the rating questions like the other groups.

The other treatment is the forced-implementation group. In this case, participants are simply given the news that "the government has recently allowed autonomous cars to make ethical decisions." Then, subjects are asked to choose whether they (i) disagree with the new laws or (ii) accept the judgment from the experts working with the government. After judging the new policy, participants proceed with the rating questions like the other groups. At the end of the experiment, to avoid misinforming the participants, both treatment groups were told that no such law or referendum is being discussed

[15] This happened during the COVID-19 pandemic.

in reality and were asked to confirm their understanding of the disclaimer.

Preamble to Experiments

Before either of the two experiments, the respondents were asked to read a comprehensive introduction. At the end of the introduction, there was a quiz with three questions that captured the most relevant part of the introduction. Those questions were: (*i*) "Is the driver experienced or a beginner?" for those answering questions about human drivers and "Is the driver a human or an AI?" for those answering questions about autonomous cars; (*ii*) "Is it possible to save both groups of people?," referring to sets A and B of pedestrians; and (*iii*) "Who is making the ethical decision, a third party or you?" Respondents were not allowed to continue until they answered the quiz perfectly.

After the quiz, there was one practice question identical to the format of the indirect questions. However, after the respondent's evaluation (from one to five stars), we asked them to confirm the meaning of their answer. For instance, those who gave a one-star rating were asked to confirm: "you have selected one star, meaning that you totally disagree with the driver's decision. Is that correct?" Then, the respondents could confirm or go back to answer the same question again.

4 Data Collection

Our main source of respondents is university students. We contacted faculty members from several universities in different parts of the world and asked them for help. Of those who replied, we asked them to conduct our survey, which took no more than fifteen minutes, during a lecture (or during the break between lectures). In addition, we shared links on social media and collected data from anonymous respondents. Finally, because of the COVID-19 pandemic, we were unable to get inclassroom respondents for half of the sample for the second experiment; thus, we used Amazon's Mechanical Turk services to get additional respondents. Table 2 summarizes the locations and dates of the interventions.

Table 2: Data Source

Experiment one

Location	Data Source	Date	Participants	Utilitarians	% Utilitarians
Bangladesh	Jahangirnagar U	4/23/2019	165	99	60.00%
Bolivia	Catholic U. of Bolivia	2/12/2019	28	18	64.29%
China	Shanghai Tech	5/17/2019	36	26	72.22%
Indonesia	Sepuluh Nopember	5/23/2019	72	53	73.61%
Brazil	PUC-Rio	3/15/2019	26	20	76.92%
India	BITS Pilani U	4/24/2019	29	16	55.17%
Japan	Shimane U	12/13/2018* 4/23/2019*	91	58	63.74%
Social Media	N/A	N/A	82	43	52.44%
			529	333	62.95%

Experiment two

Location	Data Source	Date	Participants	Utilitarians	% Utilitarians
Bolivia	Catholic U. of Bolivia	9/23/2019	133	100	75.19%
Japan	Tohoku University	7/1/2020	136	100	73.53%
India	Mechanical Turk	N/A	124	61	49.19%
United States	Mechanical Turk	N/A	170	124	72.94%
			563	385	68.38%

* We conducted experiment one of the study two times at Shimane University because we did not include types b and c during the first intervention. When a university was repeated, we made sure that participants were not repeated. Data from Mechanical Turk was gathered during the COVID-19 pandemic.

The experiments at universities were conducted in classrooms except for Tohoku University, where the survey happened online but still right after finishing the lecture. Students were not allowed to talk to each other, and they knew beforehand that 10% of the class would win a prize of approximately 20 USD for which only serious respondents would be eligible.[16] Namely, two conditions had to be met to

[16] Roughly speaking, a prize was awarded to 10% of the registered students. However, because of a lack of attendance and ineligibility resulting from "bad responses," the effective probability of winning the prize was nearly 20%. This means that the expected hourly payment was approximately 16 USD.

be eligible for the prize. First, the respondent had to provide a way to be identified (generally, student ID or email address). Second, they were asked to complete the questionnaire in a "serious way." That is, we informed the student that we had (undisclosed) methods to identify who was not answering responsibly. Although we did not inform the students of the methods used to identify reliable answers, we decided on those methods privately and in advance (which we subsequently describe).

Instead of a lottery, respondents from Mechanical Turk received a fixed payment.[17] For social media respondents, we did not offer any payments.[18] Finally, as an additional filter to potentially improve our results, we labeled some respondents as "bad." This label does not necessarily mean incorrect but, instead, means that the respondent did not provide the expected "utilitarian" answers. This categorization followed two criteria:

1) People who selected a rating of 3 or more stars for any of questions 5, 10, or 15 are considered bad respondents.

2) Respondents who took an average of fewer than five seconds to answer each question are considered bad respondents.

5 Estimating Preferences

Indirect Method

First, we test whether a bias against AI exists by asking respondents to rate drivers' ethical decisions. If such a bias exists, respondents should, on average, give a lower rating to the decisions of the self-

[17] Payments averaged 2.5 USD to complete the task. Since the task takes less than fifteen minutes to complete, the average payment per hour is at least 10 USD.

[18] Because social media data are regarded as secondary, we explain the details in the appendix C.

driving car. Let us recall that $T_1 = 1$ when the question involves AI, and let us define the star rating $y_1 \in \{1, 2, 3, 4, 5\}$ as the outcome variable. Then, we want to estimate the average treatment effect of T_1:

$$y_1 = \beta_0 + \beta_1 T_1 + \epsilon$$

Table 3 summarizes the results for the indirect method of experiment one. Surprisingly, respondents showed no bias against AI. This result was completely unexpected and counterintuitive. Moreover, these findings are very robust across different sub-samples and specifications. Although not significant, the coefficients are positive, hinting that many humans actually favor having ethical decisions made by AI rather than by other humans.[19] The only case in which we found a negative but still not significant estimate was on the sub-sample that exclusively looked at the M group, in column (5). Let us recall that respondents in this group first answered questions involving a human driver and then repeated the same scenarios but with an autonomous car. One can clearly see that we were "forcing" respondents to have a bias against AI. Indeed, some respondents showed that bias.

Direct Method

From the previous analysis, the results show that the average respondent from several countries included in our sample tends to be indifferent between AI or humans making ethical decisions. This contradicted our initial guess and the findings in Bigman and Gray (2018). However, it makes sense to claim that, although people are unconsciously willing to accept AI's ethical decision making, they are also concerned about (what they believe is) the social consensus. To test this hypothesis, we asked

[19] A sub-sample analysis shows that countries have no significant bias or, in a couple of cases, a slight positive bias in favor of AI; see appendix Table A1.

Table 3: Experiment one, indirect question

	y_1=Star rating for driver				
	(1)	(2)	(3)	(4)	(5)
AI driver ($T_1 = 1$)	0.103	0.0970	0.154	0.0822	-0.0996
	(0.0840)	(0.0984)	(0.127)	(0.0823)	(0.0604)
constant	2.727***	2.537***	2.904***	2.944***	3.047***
	(0.0425)	(0.0562)	(0.0786)	(0.0637)	(0.160)
observations	5,547	3,525	2,496	3,480	984
non-utilitarians	✓				
mixed group				✓	Exclusively
questions 5, 10 & 15	✓	✓			
unpaid respondents	✓	✓			

Errors were clustered by experiment location for the targeted data and by country for the social media data. Robust standard errors are in parentheses. * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$. y_1 is the star rating that takes a value between 1 and 5. A high value of y_1 means that the respondent agrees with the driver's ethical decision.

three different types of direct questions.

At the end of the questionnaire, respondents were asked to rate their level of agreement with a statement declaring whether we (humans) should allow a certain type of driver to make ethical decisions. $T_2 = 1$ means that the question involves AI, and $T_2 = 0$ means that the driver is human. Moreover, this question is also sub-divided into three (mutually exclusive) categories, T_{2a}, T_{2b}, and T_{2c}, displayed in Table 4. In summary, respondents in T_{2a} were asked to rate the most general statement. Respondents in T_{2b} were explicitly instructed to focus on their preferences and not on social preferences. Finally, respondents in T_{2c} were explicitly instructed to provide (their beliefs about) social preferences rather than their preferences. Common sense dictates that people are afraid of technology. Consequently, respondents should agree less with the statements with an AI driver. Table 5 shows that, disregarding the subcategories a, b, and c, respondents indeed showed some bias against AI when asked a direct opinion.

Table 4: Direct questions of experiment one

	T_2=0 driver is human	T_2=1 driver is AI
Type a	It is acceptable that **experienced drivers** are allowed to make ethical decisions.	It is acceptable that **autonomous cars** are allowed to make ethical decisions.
Type b	Regardless of what society may think, according to your personal opinion, it is acceptable that **experienced drivers** are allowed to make ethical decisions.	Regardless of what society may think, according to your personal opinion, it is acceptable that **autonomous cars** are allowed to make ethical decisions.
Type c	Regardless of your personal opinion, according to society, it is acceptable that **experienced drivers** are allowed to make ethical decisions.	Regardless of your personal opinion, according to society, it is acceptable that **autonomous cars** are allowed to make ethical decisions.

Table 5: Experiment one, direct question

	y_2=Level of agreement with statement				
	(1)	(2)	(3)	(4)	(5)
Statement on AI	-0.662***	-0.766***	-0.744***	-0.761***	-0.737***
drivers (T_2=1)	(0.0896)	(0.139)	(0.162)	(0.204)	(0.155)
Previous indirect				-0.168	-0.257
question (T_1=1)				(0.129)	(0.173)
constant	3.665***	3.682***	3.744***	3.755***	3.833***
	(0.106)	(0.123)	(0.120)	(0.119)	(0.140)
observations	528	333	290	208	290
non-utilitarians	✓				
unpaid respondents	✓	✓			
controlled by				T1 pure	T1 mixed

Errors were clustered by experiment location for the targeted data and by country for the social media data. Robust standard errors are in parentheses. * p< 0.05, ** p< 0.01, *** p< 0.001. y_2 is the star rating on a statement regarding the acceptance of a driver making ethical decisions and takes values between 1 and 5. A low value of y_2 means that the respondent is averse to accepting the ethical decision making of a certain driver.

The result that T_2 is significant and negative (as dictated by common sense) is robust under different specifications. This result states that humans are afraid of AI. However, the results in table 3 indicate that humans are willing to accept this new technology. Why do we have this discrepancy? The answer lies in the methodology. The results in table 3 were derived from an indirect way of revealing preferences, and the results in table 5 are from a direct approach. We claim that a direct approach introduces noise. Respondents answer based on a convex combination of their preferences and (their beliefs about) the preferences of society. Anticipating this reasoning, we divided the second treatment into three slight variations and explored this differentiation below.

Table 6 differentiates the types of statements being evaluated by respondents. In this table, T_2 captures the average effect of the type a question compared with the control group (human driver), while T_{2b} and T_{2c} capture the additional effect of those differentiated treatments compared with T_{2a}. The coefficient for T_2 is significant and negative. Therefore, group T_{2a} responds differently compared with respondents who are asked to state their level of agreement on statements about human drivers. The coefficient for T_{2b} is positive, which means that group b is statistically different from group a within the subset of respondents who evaluate statements of AI drivers. More precisely, the answers to the question that does not explicitly ask respondents to separate their opinion from those of society are harsher to AI compared with the answers to the question that explicitly indicates respondents to focus on their opinions (rather than those of society).

For example, if the coefficient of T_2 equals -1, that means that people give one less point on a 5-star rating to the statement that *AI should be allowed to make ethical decisions* relative to a human driver. In addition, if the coefficient for T_{2b} is $+0.5$, then people give about half less stars on a 5-star rating to the statement that *regardless of what society may think, according to my own personal preferences, AI should be allowed to make ethical decisions.* In other words, people's distrust

Table 6: Experiment one, three types of the direct question

	y_2=Level of agreement with statement				
	(1)	(2)	(3)	(4)	(5)
Statement on AI	-0.797***	-0.965***	-0.978***	-1.055***	-0.963***
drivers (T2=1)	(0.123)	(0.164)	(0.187)	(0.204)	(0.176)
T_{2b}=1	0.419***	0.524**	0.545**	0.577**	0.538**
	(0.131)	(0.178)	(0.171)	(0.172)	(0.164)
T_{2c}=1	-0.0194	0.0490	0.163	0.345	0.144
	(0.192)	(0.227)	(0.223)	(0.226)	(0.215)
Previous indirect				-0.167	-0.255
question (T1=1)				(0.126)	(0.172)
constant	3.665***	3.682***	3.744***	3.755***	3.832***
	(0.106)	(0.124)	(0.120)	(0.112)	(0.140)
observations	528	333	290	208	290
non-utilitarians	✓				
unpaid respondents	✓	✓			
controlled by				T1 pure	T1 mixed

Errors were clustered by experiment location for the targeted data and by country for the social media data. Robust standard errors are in parentheses. * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$. y_2 is the star rating on a statement regarding the acceptance of a driver making ethical decisions and takes values between 1 and 5. A low value of y_2 means that the respondent is averse to accepting the ethical decision making of a certain driver.

for AI is still present but is less severe when asked to isolate their personal preferences from those of society. In contrast, the coefficient for T_{2c} is not significant, meaning that people's distrust for AI without explicitly mentioning whose preferences they should interpret is not statistically different from that same distrust when explicitly asking them to provide society's preferences. This hints that a direct general question (type a) is probably interpreted as a question about society and not personal preferences, at least for questions about ethics.

6 Social Weights

Based on the previous results, we argue that there is some sort of social weight embedded when answering the unconstrained (type a) question. In this section, we propose a method to estimate that social weight. Let $U_i(s, T)$ be the individual valuation of a statement $s \in \{a, b, c\}$ that depends on treatment $T \in \{human\ driver, autonomous\ car\}$.[20] It depends on the respondents' own values $v_i(T)$, beliefs about society's values $\overline{v}(T)$, and possibly some bias mostly from being part of an experiment $\eta(T)$. Moreover, although the relative weights of the former two are a matter of the respondent's interpretation of what statement s says, the bias for being on an experiment is something that the respondent incorporates unconsciously. Namely, let $\lambda(s)$ and ϕ be numbers between 0 and 1 that measure the relative weight given to social preferences and unconscious bias from being part of an experiment, respectively. Then, we propose a simple functional form as follows:

$$U_i(s, T) = \phi\big[(1 - \lambda(s))v_i(T) + \lambda(s)\overline{v}(T)\big] + (1 - \phi)\eta(T) + \epsilon_i \tag{1}$$

Moreover, the relative weight $\lambda(s)$ is given by:

[20] To simplify the notation, in this section, T refers to the second treatment or T_2.

$$\lambda(s) = \begin{cases} \hat{\lambda}\,, \text{for type } a \text{ question} \\ 0\,, \text{for type } b \text{ question} \\ 1\,, \text{for type } c \text{ question} \end{cases}$$

That is, type b questions force the respondents to consciously report their preferences, type c questions force the respondents to consciously report their beliefs regarding social preferences, and we are interested in measuring the implicit social weight $\hat{\lambda}$. Namely, when the type a question is asked, respondents do not know whether to interpret it as a question that asks about their preferences or what society would accept; therefore, their answer depends on a combination of both: $U_i(a,T) = \phi\left((1-\hat{\lambda})v_i(T) + \hat{\lambda}\overline{v}(T)\right) + (1-\phi)\eta(T) + \epsilon_i$.

The model has several parameters to estimate: $v_i(0)$, $v_i(1)$, $\overline{v}(0)$, $\overline{v}(1)$, $\eta(0)$, $\eta(1)$, ϕ, and $\hat{\lambda}$. Consequently, not all of them can be identified. However, it is possible to estimate the most relevant one: $\hat{\lambda}$. First, note that the treatment only takes two values. Therefore, the curvature of function v_i and $\overline{v}$ is not important, and a linear representation of the econometric model suffices. We use OLS and an ordered logit.[21] Finally, although v_i can be heterogeneous among individuals, we assume that $\hat{\lambda}$ is homogeneous. Therefore, we estimate:

$$U_i(s,T) = \theta_0 + (\theta_1 + \theta_2 I_b + \theta_3 I_c)T + \epsilon_i \tag{2}$$

where T is a dummy that indicates whether the question addressed the control (human driver) or treatment (AI) group, and I_s indicates whether the statement was *type* s. Indeed, we solve for each of the three types and obtain the following expressions:

[21] Indeed, the OLS estimation is the same as that on table 6.

$$U_i(s,T) = \begin{cases} \theta_0 + \theta_1 T + \epsilon_i & \text{, for type } a \text{ question} \\ \theta_0 + \theta_1 T + \theta_2 T + \epsilon_i & \text{, for type } b \text{ question} \\ \theta_0 + \theta_1 T + \theta_3 T + \epsilon_i & \text{, for type } c \text{ question} \end{cases}$$

If we equate the corresponding expressions in (1) and (2) and then subtract the resulting type a equation from the types b and c equations, we obtain the two following identities:

$$\phi\hat{\lambda}(v_i(T) - \overline{v}(T)) = \theta_2 T$$

$$\phi(1-\hat{\lambda})(\overline{v}(T) - v_i(T)) = \theta_3 T$$

Evaluating at $T = 1$, we obtain $\frac{1-\hat{\lambda}}{\hat{\lambda}} = -\frac{\theta_3}{\theta_2}$, or:

$$\hat{\lambda} = \frac{\theta_2}{\theta_2 - \theta_3} \tag{3}$$

Table 7 shows the OLS estimation of (2) and the ordered logit when the log-odds ratio follows that same equation. In both cases, the treatment (T_2 in this case) is significant and positive. That is, asking respondents their level of agreement with allowing self-driving cars versus explicitly asking them to focus on their preferences by ignoring social preferences on the same issue yields different results. More importantly, we use equation (3) to compute the social weight and test whether $\hat{\lambda}$ is statistically different from zero and one. The p-values show that, at 5% confidence, $\hat{\lambda}$ is statistically different from zero but cannot be distinguished from one. That is, the social weight assigned when answering type a questions is not zero, and it might be a large number, close to one.

Table 7: Social weights

	y_2=Level of agreement with statement			
	OLS		Ordered logit	
	(1)	(2)	(3)	(4)
Statement on AI	-0.965***	-0.797***	-1.317***	-1.079***
drivers (T_2=1)	(0.164)	(0.123)	(0.294)	(0.217)
T_{2b}=1	0.524**	0.419***	0.799***	0.645***
	(0.178)	(0.131)	(0.260)	(0.188)
T_{2c}=1	0.0490	-0.0194	0.131	-0.0144
	(0.227)	(0.192)	(0.303)	(0.257)
constant	3.682***	3.665***	–	–
	(0.124)	(0.106)	–	–
observations	333	528	333	528
non-utilitarians		✓		✓
$\hat{\lambda}$	1.103	0.956	1.196	0.978
$p[\hat{\lambda} = 0]$	0.027	0.024	0.013	0.011
$p[\hat{\lambda} = 1]$	0.836	0.917	0.684	0.955

Errors were clustered by experiment location for the targeted data and by country for the social media data. Robust standard errors are in parentheses. * p< 0.05, ** p< 0.01, *** p< 0.001. y_2 is the star rating on a statement of the acceptance of a driver making ethical decisions and takes values between 1 and 5. A low value of y_2 means that the respondent is averse to accepting a certain driver's ethical decision making.

This positive social weight partially explains why the estimations from a direct and an indirect method different. Nevertheless, Table 6 shows that the statement that explicitly asks for personal preferences does not completely eliminate the bias against AI (i.e., there is about a half-star point that is not explained). Next, we discuss one possible reason for the remaining unexplained discrepancy between the direct and indirect methods.

7 Policy and Implementation

The contrasting results from the direct and indirect method hint at the idea that, when being directly asked for their opinion, people may have a bias against AI. At the same time, when being forced to accept the existence of AI in their lives, people may not really have concerns. Thus, perhaps a status quo effect may affect our results.[22]

This idea is explored in a second round of experiments. In experiment two, we focus on indirect questions, and respondents exclusively evaluate AI drivers. The control group of experiment two is identical to the treatment group of experiment one. In contrast, the treatments are two alternative ways to introduce AI ethical decision making by a hypothetical government: a forced implementation and implementation via a plebiscite. Regarding the forced implementation, the government already decided to allow autonomous cars to make ethical decisions. Then, prior to evaluating the ethical decisions of the AI (as before), respondents are asked whether they support the government's decision. On the plebiscite, again, prior to evaluating the ethical decisions of the AI, respondents are given the option to vote on a referendum that asks whether they want to allow AI ethical decision making into cars.

[22](See, for example, Kahneman and Tversky, 1979).

In both cases, respondents can be in favor of or against the technology. However, the difference is that, in the former case, the policy is already implemented. In the latter case, the policy has not yet been implemented; thus, the status quo is different. More specifically, in the plebiscite case, respondents implicitly know that the status quo is not having AI ethical decision making and that their vote can change the outcome. Nevertheless, the voting is not really counted, and the outcome of the referendum is always to allow autonomous cars. However, respondents do not know this at the moment of voting.

Let us aggregate both treatments as one variable called *information* = either referendum or forced implementation. Moreover, following basically any index on development or trust in a government, we divided our sample into two groups: "good institutions" for Japan and the United States and "bad institutions" for Bolivia and India. We interacted this sample categorization with the treatment of experiment two. The results for this second experiment are shown in Table 8. Columns (1) and (4) indicate that, in the entire sample, explicitly mentioning the introduction of AI ethical decision making does not make a difference. However, columns (2) and (3) show that discussing the implementation of AI increases people's opinion in favor of AI in places with good institutions but decreases people's opinion of AI in places with poor institutions. Moreover, as shown in columns (5) and (6), this differentiation seems stronger when given the option to "vote" on the issue.[23]

Finally, we check how our results depend on whether the respondent was initially in favor or against the introduction of the new technology. More precisely, the group "in favor" is either those who voted "yes" in the referendum or those who responded that they would accept the introduction of AI by the government. Similarly, the group "against" is either those who voted "no" in the referendum or

[23]Note that, as shown in appendix Table A1, the sub-sample analysis of the indirect questions in experiment one was more homogeneous; that is, countries either had no significant effect or had a positive effect.

Table 8: Policy implementation

	y_3=Star raring for AI on experiment two					
	(1)	(2)	(3)	(4)	(5)	(6)
Information	0.0118					
	(0.0679)					
× good institutions		0.0863***	0.158***			
		(0.0138)	(0.0162)			
× bad institutions		-0.0979	-0.185***			
		(0.0869)	(0.0192)			
Option to vote				0.0454		
				(0.144)		
× good institutions					0.276***	0.305**
					(0.0229)	(0.0582)
× bad institutions					-0.219***	-0.377*
					(0.0231)	(0.121)
Forced implementation				-0.0441		
				(0.0671)		
× good institutions					0.0478	0.147**
					(0.0508)	(0.0269)
× bad institutions					-0.149*	-0.136
					(0.0606)	(0.0602)
constant	2.538***	2.615***	3.341***	3.216***	3.342***	3.398***
	(0.0479)	(0.0612)	(0.0127)	(0.0679)	(0.0104)	(0.0603)
observations	5,775	5,775	8,444	8,444	8,444	4,844
non-utilitarians			✓	✓	✓	✓
sample	all	all	all	all	all	age<30

Errors were clustered by experiment location for the targeted data and by country for the social media data. Robust standard errors are in parentheses. * p< 0.05, ** p< 0.01, *** p< 0.001. y_3 is the star rating to AI drivers on experiment two, and it takes a value between 1 and 5. A high value of y_3 means that the respondent agrees with the ethical decision of the AI.

Table 9: Response to policy implementation

	y_3=Star raring for AI on experiment two			
	(1)	(2)	(3)	(4)
In favor	0.0412			
	(0.0389)			
× voted		0.0583		
		(0.0729)		
× good institutions			0.149***	0.139***
			(0.0221)	(0.0232)
× bad institutions			-0.0674	-0.141***
			(0.0720)	(0.00251)
× forced		0.0247		
		(0.0241)		
× good institutions			0.0374	0.151
			(0.0331)	(0.0955)
× bad institutions			0.0277***	0.0489***
			(0.00112)	(0.00750)
Against	-0.0341			
	(0.103)			
× voted		-0.0207		
		(0.163)		
× good institutions			0.174**	0.182*
			(0.0344)	(0.0640)
× bad institutions			-0.0156	0.00952
			(0.0379)	(0.0700)
× forced		-0.0461		
		(0.0509)		
× good institutions			-0.282	-0.414***
			(0.180)	(0.0657)
× bad institutions			-0.108	-0.153**
			(0.0812)	(0.0423)
constant	2.535***	2.533***	2.606***	2.604***
	(0.0421)	(0.0467)	(0.0502)	(0.0168)
observations	5,775	5,775	5,775	3,540
sample	all	all	all	age< 30

Errors were clustered by experiment location for the targeted data and by country for the social media data. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All columns exclude non-utilitarian respondents. y_3 is the star rating for AI drivers in experiment two, and it takes a value between 1 and 5. A high value of y_3 means that the respondent agrees with the ethical decision of the AI.

responded that they would reject the introduction of AI by the government. Columns (1) and (2) of Table 9 show that, in the entire sample, being in favor or against the introduction of AI does not make any difference when evaluating the decisions of the AI, which still holds after isolating the effects of having the option to vote or being forced to accept the new technology.

However, columns (3) and (4) of table 9 show that, in countries with good institutions, having the right to vote gives people more trust of AI. Additionally, in countries with good institutions, people younger than 30 in the forced implementation group who were initially against the introduction of AI more harshly evaluated the decisions of the autonomous car than the control group (no explicit mentioning of the introduction of AI). Finally, in countries with poor institutions, respondents who were initially in favor of AI and were forced to accept the new technology increased their evaluation of decisions related to the autonomous car, whereas those who were given the option to vote rated more harshly the decisions of the autonomous car.

8 Conclusions

We studied how society would react to the introduction of AI ethical decision making. In the first experiment, we measure the bias against AI using a direct and an indirect method to reveal preferences. In the second experiment, we test the effect of two different alternative policies to introduce AI into society.

The results from experiment one show that when asking directly about their opinion on whether we should allow a certain driver to make an ethical decision, respondents had a negative bias toward AI. In contrast, when asking indirectly, by requesting respondents to rate the ethical decision making of a certain driver, there was no such bias. Moreover, because we had three different types of direct questions, we were able to identify the weight that respondents put on their answer when facing the more general and "open to interpretation" question. Indeed, that social weight is positive and close to one.

In addition, experiment two explores the effect of two ways to introduce AI into society: a plebiscite and a forced implementation. In contrast to the control group in which the introduction of AI to society is not explicitly discussed, we observe that respondents in countries with strong institutions improve their perception about AI, whereas respondents in countries with poor institutions worsen their perception about AI. Moreover, this effect is stronger in magnitude within the plebiscite group than the forced implementation group.

People seem not to reject the idea of ethical decision making by AI. However, when asked their opinion on this issue, there is an aversion toward AI. Are we ready for AI ethical decision making? At least in the case of autonomous cars, society does not seem to mind such decision making, at least conditional on the technology already implemented. However, society also seems to be better off by not "having that conversation." Unfortunately, it is a discussion that will happen eventually, if not with autonomous cars, then with other, more advanced robots.

Appendix

A Additional Tables

Table A1: Indirect question, sub-sample analysis by country

	y_1=Star rating for driver			
	(1)	(2)	(3)	(4)
AI driver ($T_1 = 1$)	0.109	0.383***	0.822*	0.274
	(0.0794)	(0.139)	(0.432)	(0.189)
constant	2.576***	2.957***	2.444***	2.861***
	(0.137)	(0.103)	(0.401)	(0.0952)
observations	2,820	852	132	168
heterogeneity	Country F.E.	Bangladesh	Bolivia	Brazil
	(5)	(6)	(7)	(8)
AI driver ($T_1 = 1$)	-0.513	-0.0833	-0.149	0.151
	(0.355)	(0.275)	(0.210)	(0.150)
constant	2.898***	2.972***	3.162***	2.705***
	(0.174)	(0.207)	(0.116)	(0.100)
observations	204	144	456	540
heterogeneity	China	India	Indonesia	Japan

In all columns, we excluded bad respondents—questions 5, 10, 15, and the M group. Errors were clustered by respondent. Robust standard errors are in parentheses. * $p< 0.05$, ** $p< 0.01$, *** $p< 0.001$. y_1 is the assessment of the driver's decision and takes values between 1 and 5. A high value of y_1 means that the respondent agrees with the ethical decision of the driver.

Table A2: Summary of the Experiment

Experiment one

	Human Driver (Control)	AI Driver (Treatment)	Mixed (Treatment)
Introduction	✓	✓	✓
Vote on referendum			
Opinion on new laws			
Indirect questions (assessment of ethical decisions)	✓	✓	✓
Direct question (degree of agreement with a statement)	✓	✓	✓
Disclaimer on misinformation			

Experiment two

	AI Driver (Control)	Referendum (Treatment)	Forced implementation (Treatment)
Introduction	✓	✓	✓
Vote on referendum		✓	
Opinion on new laws			✓
Indirect questions (assessment of ethical decisions)	✓	✓	✓
Disclaimer on misinformation		✓	✓

B Instructions for the Experiment in Universities

The following text represents the directions that we provided to the person proctoring the experiments:

For the Students:

You will participate in a study on ethical decision making. The questionnaire will begin with an introduction explaining what the study consists of and how to answer it. Then you will be asked to answer 15 questions about ethical decisions. The questionnaire requires the internet and can be answered on computers, smartphones, and tablets. The original format is in English, but there is a button in the upper right corner to change the language. We have methods to detect who answers the questionnaire seriously and who does not. We will randomly select N students[24] who answered the questionnaire seriously, and these students will earn 20 USD[25]. If you wish to participate in the raffle, you must provide your student ID or email or full name for the last question on the first page of the questionnaire. Thank you for participating.

For the Instructor:

Please do not mention anything that is not in the students' instructions. In particular, do not explain the treatment and control groups. Please do not allow students to talk to each other.

[24] N was the rounded-up integer that corresponds to 10% of the registered students in the class.
[25] Or a similar amount in local currency. The payment was in either cash or giftcards.

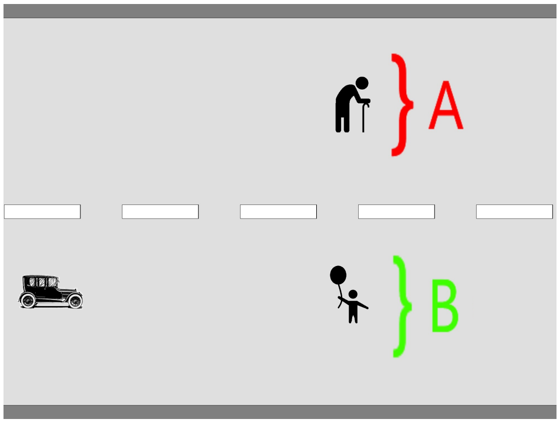
C Social Media Data

We shared via email links leading directly to the questionnaire. In addition, we shared links on social media with a brief description of the questionnaire (without giving away information on the treatment and control groups). Moreover, there were three different lengths of questionnaires: 5, 10, or 15 questions. We decided to do so because we were not attracting respondents when there was only the option to fill out the long (15 questions) questionnaire. The link shared via email was the 15-question version. In addition to length modifications, an introduction to the questionnaire was reduced, and the examples were removed because we observed that some respondents started but never completed the questionnaire.

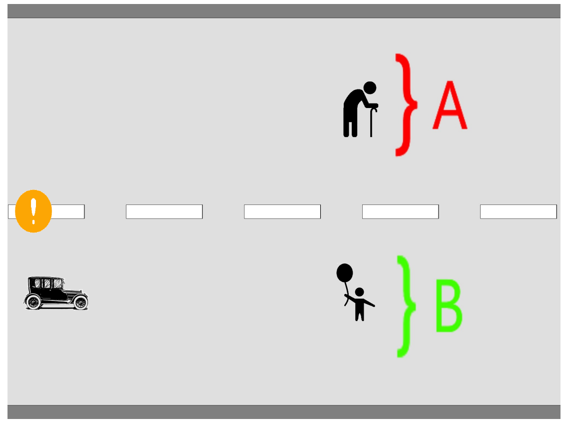
D Questionnaire

We asked some basic information, such as age, education, country of residency, country of origin, political view, and religion. However, answering those questions was not mandatory. Then, we provided an introduction that explains the topic and types of questions. To guarantee that the respondents understood the tasks, we also included a quiz about the directions and a question "zero" that confirms whether the respondents would answer the questionnaire correctly. After this, the questionnaire moves to the 15 actual questions on ethical decision making. They were shown an animated image in which a car switches lanes to save set B of randomly selected people, thereby saving their lives. However, this means that the car will necessarily crash into set A of randomly selected people. The animation shows a loop of the four images displayed in Figure A1.

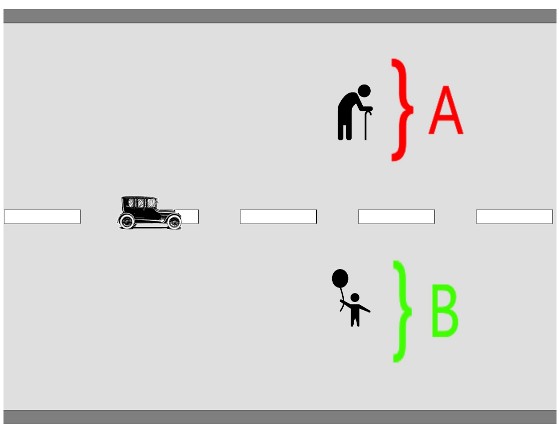
Figure A1: Sequence of images shown in animated questionnaire



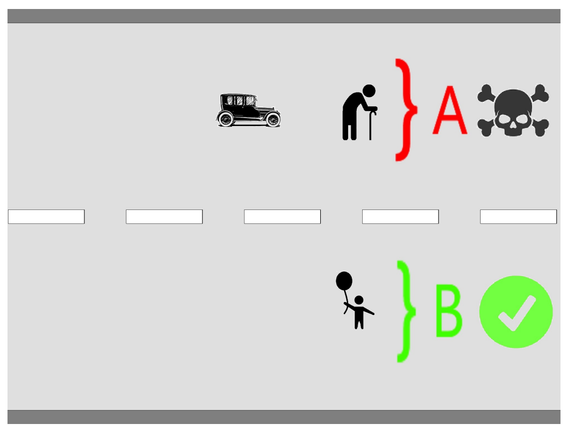
(a)



(b)



(c)



(d)

The animated image displays how a car (a) realizes it has an unexpected ethical dilemma (b), then it chooses to switch lanes (c), and saves set B of people at the cost of harming set A of people (d).

References

Asimov, Isaac (1942) "Runaround," *Astounding Science Fiction*, Vol. 29, pp. 94–103.

Bateman, Ian J, MA Cole, Stavros Georgiou, and DJ Hadley (2006) "Comparing contingent valuation and contingent ranking: A case study considering the benefits of urban river water quality improvements," *Journal of environmental management*, Vol. 79, pp. 221–231.

Beshears, John, James J Choi, David Laibson, and Brigitte C Madrian (2008) "How are preferences revealed?" *Journal of public economics*, Vol. 92, pp. 1787–1794.

Bigman, Yochanan E and Kurt Gray (2018) "People are averse to machines making moral decisions," *Cognition*, Vol. 181, pp. 21–34.

Bonnefon, Jean-François, Azim Shariff, and Iyad Rahwan (2016) "The social dilemma of autonomous vehicles," *Science*, Vol. 352, pp. 1573–1576.

Bourget, David and David J Chalmers (2014) "What do philosophers believe?" *Philosophical studies*, Vol. 170, pp. 465–500.

Boxall, Peter C, Wiktor L Adamowicz, Joffre Swait, Michael Williams, and Jordan Louviere (1996) "A comparison of stated preference methods for environmental valuation," *Ecological economics*, Vol. 18, pp. 243–253.

Gogoll, Jan and Julian F Müller (2017) "Autonomous cars: in favor of a mandatory ethics setting," *Science and engineering ethics*, Vol. 23, pp. 681–700.

Goodall, Noah J (2014) "Machine ethics and automated vehicles," in *Road vehicle automation*: Springer, pp. 93–102.

Goodrich, Michael A, Alan C Schultz et al. (2008) "Human–robot interaction: a survey," *Foundations and Trends® in Human–Computer Interaction*, Vol. 1, pp. 203–275.

Hensher, David A and Mark Bradley (1993) "Using stated response choice data to enrich revealed preference discrete choice models," *Marketing Letters*, Vol. 4, pp. 139–151.

Kahneman, Daniel and Amos Tversky (1979) "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, Vol. 47, pp. 263–291.

Karásek, Matěj (2020) "Good vibrations for flapping-wing flyers," *Science Robotics*, Vol. 5.

Lin, Patrick (2016) "Why ethics matters for autonomous cars," in *Autonomous driving*: Springer, Berlin, Heidelberg, pp. 69–85.

Malle, Bertram F (2016) "Integrating robot ethics and machine morality: the study and design of moral competence in robots," *Ethics and Information Technology*, Vol. 18, pp. 243–256.

Malle, Bertram F, Matthias Scheutz, Thomas Arnold, John Voiklis, and Corey Cusimano (2015) "Sacrifice one for the good of many?: People apply different moral norms to human and robot agents," in *Proceedings of the tenth annual ACM/IEEE international conference on human-robot interaction*, pp. 117–124, ACM.

McCarthy, John and Patrick J Hayes (1981) "Some philosophical problems from the standpoint of artificial intelligence," in *Readings in artificial intelligence*: Elsevier, pp. 431–450.

McDermott, Drew (2011) "What matters to a machine," *Machine ethics*, pp. 88–114.

Miller, Klaus M, Reto Hofstetter, Harley Krohmer, and Z John Zhang (2011) "How should consumers' willingness to pay be measured? An empirical comparison of state-of-the-art approaches," *Journal of Marketing Research*, Vol. 48, pp. 172–184.

Navarrete, C David, Melissa M McDonald, Michael L Mott, and Benjamin Asher (2012) "Virtual morality: Emotion and action in a simulated three-dimensional "trolley problem".," *Emotion*, Vol. 12, p. 364.

Noothigattu, Ritesh, Snehalkumar S Gaikwad, Edmond Awad, Sohan Dsouza, Iyad Rahwan, Pradeep Ravikumar, and Ariel D Procaccia (2018) "A voting-based system for ethical decision making," in *Thirty-Second AAAI Conference on Artificial Intelligence*.

Nyholm, Sven and Jilles Smids (2016) "The ethics of accident-algorithms for self-driving cars: an applied trolley problem?" *Ethical theory and moral practice*, Vol. 19, pp. 1275–1289.

Riek, Laurel and Don Howard (2014) "A code of ethics for the human-robot interaction profession," URL: https://ssrn.com/abstract=2757805.

Scarpa, Riccardo, Eric SK Ruto, Patti Kristjanson, Maren Radeny, Adam G Drucker, and John EO Rege (2003) "Valuing indigenous cattle breeds in Kenya: an empirical comparison of stated and revealed preference value estimates," *Ecological Economics*, Vol. 45, pp. 409–426.

Veisten, Knut (2007) "Willingness to pay for eco-labelled wood furniture: Choice-based conjoint analysis versus open-ended contingent valuation," *Journal of forest economics*, Vol. 13, pp. 29–48.

Wardman, Mark (1988) "A comparison of revealed preference and stated preference models of travel behaviour," *Journal of transport economics and policy*, Vol. 22, pp. 71–91.

Whitehead, John C, Christopher F Dumas, Jim Herstine, Jeffery Hill, and Bob Buerger (2008) "Valuing beach access and width with revealed and stated preference data," *Marine Resource Economics*, Vol. 23, pp. 119–135.

Wiener, Norbert (1964) *God and Golem, Inc: A Comment on Certain Points where Cybernetics Impinges on Religion*, Vol. 42: MIT press.

Zaller, John and Stanley Feldman (1992) "A simple theory of the survey response: Answering questions versus revealing preferences," *American journal of political science*, Vol. 36, pp. 579–616.