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# Privacy, values and machines: Predicting opposition to artificial intelligence

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## Abstract

In this study we identify, for the first time, social determinants of opposition to artificial intelligence, based on the assessment of its benefits and risks. Using a national survey in Spain (n= 5,200) and linear regression models, we show that common explanations regarding opposition to artificial intelligence, such as competition and relative vulnerability theories, are not confirmed or have limited explanatory power. Stronger effects are shown by social values and general attitudes to science. Those expressing egalitarian values and privacy concerns, as well as those less predisposed to innovation in a general sense, are more prone to oppose both technological applications. Lastly, we found evidence that, as in other complex technological applications, a new cognitive shortcut is produced. In this case, we found a strong correlation (0.652,  $p < 0.001$ ) between public attitudes towards robotization in the workplace and towards artificial intelligence. We discuss the implications of this new cognitive schema, the “intelligent machine”, as a new threatening or beneficial element.

**Keywords:** privacy; individualism; labor; distrust in technology; robotization

## Introduction

A few years ago, Artificial Intelligence (AI) was just one more argument with which filmmakers used to make science fiction movies. However, today AI has become a reality, leading a great portion of the technological innovations that reach the market. The presence of the AI in our lives has been accompanied by a growing public debate about the risks and benefits that these technologies can bring to questions as wide ranging as privacy, national sovereignty and the health of democratic electoral processes (e.g. Brexit), and even new types of interactions in the workforce.

A person's attitude towards AI will determine human-AI interaction, and whether they will accept AI-based technology without criticism, with caution, or not at all. Similarly, public debate about how to regulate AI in fields such as the workplace or electoral campaigns is heavily conditioned by people's attitudes towards this new technology. Thus, our findings are of particular interest to the field of human-AI communication, as well as to those leveraging AI-based technologies in areas such as digital platforms, political communication, workforce organization and collaboration, commercial advertising, and those advancing the public debate around AI regulation.

At present, there are no empirical works that show what factors may mediate the opposition to artificial intelligence. In response, this study is the first to identify the factors affecting people's attitudes towards AI. We formulated the hypothesis based on two strands of work. First, we did a general literature review of the current understanding around opposition to controversial technologies. Hypothesis H1 through H4 and H7 arose from this review. The second approach was AI-specific, focusing on the main critical positions about the risks that may be involved in the introduction of technologies based on artificial intelligence. Hypothesis H5 and H6 resulted from this line of query.

## Theoretical framework

In contemporary societies, social representations of technoscience have become more complex, moving away from traditional optimistic representations (Allum, Sturgis, Tabourazi & Brunton-Smith, 2008; Maibach, Roser-Renouf, Smith & Dawson, 2012; Kerschner & Ehlers, 2016). Certainly, a large majority of the population expresses a positive attitude towards the central body of science and technology, but there are certain

controversial issues that are criticized by broad sectors of society (Torres-Albero & Lobera, 2017).

The interest in understanding the critical positions towards controversial technologies has been expressed in different theoretical approaches. The theory of “cognitive deficit” has traditionally been the predominant explanation (Sturgis & Allum 2004), producing a vibrant debate and disagreement among scholars, particularly in their assumption that the so-called “irrational” fears towards science and technology among some sectors of public opinion are based on their lack of scientific knowledge. At one end of the spectrum are those who believe in a purely “cognitive deficit” model and argue that this lack of knowledge explains critical positions toward science and technology (Bodmer 1985; Ziman 1991); at the other end are those who argue that there are other factors that explain this lack of support, as well as those who argue that scientific knowledge is a social construction and is difficult to quantify (Johnson 1993). Recent studies show that the effect of knowledge on acceptance cannot be generalized wholesale from one application, or method, to others (Mielby et al., 2013). Since this is the first study specific to AI, we will test the validity of the cognitive deficit model. We hypothesize that the opposition to artificial intelligence will be higher among those with lower level of scientific knowledge of the individual (**H1**).

In recent decades, other explanations have been developed that emphasize the pressure of new technological risks (Beck, 1986) as key factors in explaining critical attitudes, encompassing a growing social demand for transformation of how science and technology are socially managed (Todt, 2011; Scheufele, 2014). Some studies suggest that the effect of social trust (Priest 2001; Siegrist et al., 2000) and the level of confidence in scientists, regulators, and industry (Priest 2001) surpass the influence of the level of scientific knowledge on the perception of novel and potentially dangerous technologies. Thus, we expect a higher opposition to artificial intelligence among those with distrustful towards the appropriate functioning of science and technology (**H2**).

On the other hand, it may be argued that some individuals may characteristically resist change, i.e. be less innovative (Sheth & Stellner, 1979; Barak, 2018). This trait has been identified as a factor inhibiting the consumption of new products, as well as the adoption of new technologies in organizations (Jones, 2013). In this vein, we expect that the opposition to artificial intelligence will be higher among those less prone to innovation (**H3**).

Cultural theory points out that fears about new technologies are related to values and the maintenance of certain cultural dynamics (Douglas and Wildavsky, 1982). According to this perspective, it is not the technology that is resisted but the changes caused by it (Schein, 1985). Each social group selects what constitutes a risk, protecting certain patterns of social interaction against others. Thus, there would be a relationship between the value systems and the selection of risks manifested by different social groups.

While a small number of works have tested cultural theory, those works have shown evidence supporting its validity, particularly when flagging up the influence of egalitarian values (Carlisle & Smith, 2005). In this vein, Grendstad and Selle (1997), Ellis and Thompson (1997), and Marris, Langford and O’Riordan (1998) found that egalitarian values are associated with a greater concern about environmental issues of controversial technologies than individualist values. Thus, we expect a higher opposition to artificial intelligence among those expressing egalitarian values (**H4**).

### **Specific public concerns on AI**

We have identified two main groupings of critical positions about the risks that may be involved in the introduction of technologies based on artificial intelligence. The first set of concerns addresses to the perceived link between artificial intelligence (AI) and its everlasting effects on work and employment. There is a consensus, particularly among experts, that AI will likely outperform humans in many activities and tasks in the following years (Grace, Salvatier, Dafoe, Zhang & Evans, 2018). Nevertheless, there are differing views regarding the overall impact of AI on human life, which oscillate from celebrating its positive outcomes to apocalyptic gazes that see it as an existential threat to humanity (Sturken, Thomas & Ball-Rokeach, 2004; Madridakis, 2007), highlighting the risks of an attack against humans (individually or collectively) by technology with artificial intelligence<sup>1</sup>. The issue of employment here is critical once the fast development of robotics and the growing automation of processes should put into risk a significant number of jobs, especially among the least skilled. This has led to a media hype about the challenges of a jobless future, supported to some extent by scholarly work.

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<sup>1</sup> An example of this gloomy perspective is Elon Musk (the CEO of Tesla) commenting on AI, saying it is like “summoning the demon”. Stephen Hawking also expressed similar statements.

Some experts have been emphasizing the disruption these new developments may involve, pointing at a future with fewer jobs available and smaller payrolls for most of the workforce (Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017), while increasing the interest for basic income policies and robot taxation (Standing, 2017; Oberson, 2017). Key institutions such as the World Economic Forum or the prestigious consulting firm PwC have stated in their reports that the net effect of robotics and AI will likely create mass technological unemployment (see Upchurch, 2018). This obviously poses important challenges for the future, although the determinism of technology in this narrative should not be overlooked (Edwards & Ramirez, 2016).

Another concern has to do with the quality of jobs created in the context of an AI-based economy. So far, the labor market in the new economy is quite polarized: while AI is boosting high-skilled jobs related to computing or robotics, a new layer of low-skilled jobs and low-paid jobs linked to different app-connected and “crowd-work platforms” tasks such as delivery, customer feedback and support, transport, storage and other services has emerged (Howcroft & Bergvall-Kåreborn, 2019). New forms of work mediated by algorithms have proliferated, degrading in many cases the quality of labor (Bergvall-Kåreborn & Howcroft, 2014; Fleming, 2017).

Some researchers have suggested that while a future without work is very unlikely, as proved by previous experiences (see Upchurch, 2018), the degradation of labor conditions should be considered as a major challenge in Western economies (Spencer, 2018). In this context of labor competition, we hypothesize that higher levels of opposition to AI will be linked to higher negative impacts on employment that individuals may experience due to AI-based innovations. Thus, we expect a lower opposition to artificial intelligence among those less exposed to negative effects on work and employment: those with college education, higher household income and economically inactive (**H5**).

The second strand of worries have to do with fears about privacy in a world mediated by the World Wide Web, the rise of e-commerce and the popularity of different social networks sites (Goldfarb & Tucker, 2012). Recently, new concerns have emerged about the use of personal information in electoral processes (Ward, 2018; Raab, 2019), particularly as a means for psychological targeting in political persuasion campaigns. Certainly, the interest on the power of watching and classifying information is already present in classic authors such as Foucault (1977), and the development of new forms of

*post-panopticism* has attracted since then the interest of scholars (see Ball, Haggerty, & Lyon, 2012).

However, the increasing forms of surveillance developed in the context of the “War on Terror” (Lyon, 2007) and the rise of new-tech giants whose business models rely on the exploitation of personal data have ignited a public debate about how personal data is obtained and managed. The rapid expansion of the big data market is the result of the development of various technologies linked to the capture and storage of personal information from the internet, and may provide valuable information for consumer and social profiling. Regarding the State, the disclosure of mass surveillance leaked by Edward Snowden, the growing influence of State cyberpolicing capacities or the profiling of its citizens by the Chinese authorities are just some examples that show a discomfoting revelation about the dangerous collusion of new forms of governance and IT applications (Lyon, 2014).

Furthermore, the scandals related to the usage of data without permission in the realm of business have gained as much attention in the media. The sales of personal information without explicit permission from the users - Facebook and Cambridge Analytica - and the risk of leaking such data as the result of hacking - Ashley Madison, Facebook again - have caused outrage among the public opinion, turning the attention to the issue of privacy in a context of widespread use of personal data in the markets.

This has led to a raising awareness about personal data and the need to protect it, acknowledging that there are important risks. The application of big data problem solving to a variety of areas, from geo-localization, health monitoring through wearable devices, online shopping or banking services helps to create new business niches, but also offers potential harms to users (Morozov, 2011; Baruh & Popescu, 2017). Security breaches may end up in stolen passwords, hacked e-mail and bank accounts, industrial piracy and other dangerous outcomes.

The issue of privacy is particularly salient among online consumers, and several studies have stated that negative perceptions about how personal data is treated may affect the frequency of online transactions (Akhter, 2014). Moreover, the use of images and personal information in a context where the individual voluntarily provides that information to a corporation might lead to future disputes about copyright, data protection and ownership. All this has raised apprehension about the potential misuse of such data and growing concerns about online privacy (Cecere, Le Guel & Soulié, 2015), plus further

fears that the interconnection of different data sets from both State and industry might increase the levels of surveillance in society (Lyon, 2014).

All these concerns have led to different discussions about how to tackle the problem of privacy aside from pushing certain regulations in national and supranational levels. Lemih and Popescu (2017) suggest that the collective dimension of privacy should be acknowledged in the public sphere, which in turn would provide alternatives for privacy protection that would go beyond the current “take it or leave it” neoliberal scenario. However, it seems difficult to give clear responses given the complexity of regulating internet and the different levels of concern that individuals express. A number of investigations have actually highlighted the importance of societal factors in the apparent variances among internet privacy concerns (Thomson, Yuri & Ito, 2015; Cecere, Le Guel and Soulié, 2015), and therefore not all of social groupings share equal views on how privacy should be protected, with different views regarding cultural background, gender and age. Following this vein, we expect that opposition to artificial intelligence will be higher among those more concerned about negative effects on privacy (**H6**).

Additionally, recent studies emphasize the importance of cognitive schemas or shortcuts in the positioning on controversial technological applications (Scheufele, Corley, Shih, Dalrymple & Ho, 2009, Brossard et al., 2009; Ho, Brossard & Scheufele, 2008; Brossard and Scheufele 2008). These schemas can be understood as “prior organized knowledge, abstracted from concrete experience”, which orientate the responses of individuals to complex situations (Fiske & Linville 1980: 543), and they are organized around semantic categories of high significance (Kumlin, 2001). These approaches are in line with Dake (1991), when he emphasized the importance of *Weltanschauungen* or worldviews as “guiding dispositions” that guide the responses of individuals in complex situations. Thus, we test an eventual cognitive shortcut with benefits and risks of robotization: we expect perceptions of AI to be associated with perceptions of robotization in the workplace (**H7**).

## Methods

Our experimental design seeks to test hypotheses raised in the scientific literature on opposition to controversial technologies and those derived from critical positions towards artificial intelligence, presented above. We use data from the 9<sup>th</sup> National



Survey on the Social Perception of Science and Technology in Spain 2018. As scientific coordinators of this survey, we included questions that allow us to relate the attitudes towards artificial intelligence with individual and contextual sociodemographic variables, as well as with factors related to knowledge and opinions about science and technology. The dependent variables of our analysis have been extracted from the 15<sup>th</sup> question of the questionnaire, which asks about the degree of identification, utilizing different phrases from a scale of 1 to 5.<sup>2</sup> In the 2018 survey, a total of 5,200 personal interviews (face to face) were carried out on people who had been residents in Spain for five or more years and were 15 years of age or older (the sample size in previous editions is similar). The sampling procedure was multistaged and stratified, with selection of primary units (municipality) and secondary units (census tracts) conducted through proportional random sampling and the last units (individuals) by random routes and quotas for gender and age. The sampling error for the total sample is  $\pm 1.25\%$  for a confidence level of 95.5 %, with the assumption of simple random sampling, calculated considering non-proportional samples.

Our dependent variable (opposition towards artificial intelligence) is built as the balance between the assessment of the perception of risks and the perception of the benefits of artificial intelligence. The analyzed phrases are the following: *“Using a scale of 1 to 5, where 1 means “no risk” and 5 means “many risks”, to what extent do you think there are risks in Artificial Intelligence?”*; *“And now considering the benefits and using a scale of 1 to 5, where 1 means “no benefit” and 5 means “many benefits”, to what extent do you think Artificial Intelligence has benefits?”*. Thus, the dependent variable is constructed with the value of the risk assessment less the value of the assessment of the benefits. The distribution of this variable has a low skewness (0.066) and standard error of kurtosis (0.068), with a kurtosis value of -0,314, primarily due to a high concentration of people who consider that risks and benefits are balanced (see Appendices 1-3).

The independent variables of sociodemographic character, chosen from a review of the literature, were the following: *gender*, *age*, *college education*, *work status* (economically active or inactive), and *household income*. Also, the *level of scientific knowledge*, as pointed out by the cognitive deficit model (Bodmer 1985; Ziman 1991)

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<sup>2</sup> The questionnaire and the database of this survey are available at <https://icono.fecyt.es/informes-y-publicaciones/percepcion-social-de-la-ciencia-y-la-tecnologia-en-espana>

was included. This variable was constructed from the items of question 24 in the survey, in which it asks the respondent to choose the correct phrase for six pairs of statements:

(1) the Sun revolves around the Earth / the Earth revolves around the Sun, (2) antibiotics cure infections caused by both viruses and bacteria / antibiotics cure infections caused by bacteria, (3) the first humans lived at the same time as dinosaurs / humans never co-existed with dinosaurs, (4) eating a genetically modified fruit changes the genes of the person who eats it / eating a genetically modified fruit does not change the genes of the person who eats it, (5) current climate change is a consequence of the hole in the ozone layer / current climate change is mainly due to the accumulation of greenhouse gases, (6) the number pi ( $\pi$ ) is often used, among other things, in the manufacture of tires / the number pi ( $\pi$ ) is the relationship between the legs and the hypotenuse of a triangle. The resulting variable is continuous and takes six values, from 0 to 6 successful answers.

A second set of variables related with values and attitudes was included:

- *Egalitarianism*. We have built a continuous variable based on a question from the *European Values Study* (EVS). The respondents had to place their opinions on a 1 to 10 scale on the following pair of statements: “the state must give more freedom to business/corporations” / “the state must control companies more effectively”. High scores in this variable indicate that respondents are strongly egalitarian versus individualist (Carlisle & Smith, 2005).

- *Resistance to innovation*. This variable was built from the factorial analysis of the question Q29: (1) I often take risks to make progress in life, even when unsure of what will happen, (2) I am often open to new ideas and new ways of doing things or thinking, (3) I tend to plan the future in advance, (4) I highly value people who question traditional ways of acting, (5) I try to learn new things all the time, making learning my way of life, (6) I prefer to do important things for myself, without much help from others. The respondents used a scale where 0 means “not at all describing my way of being” and 10 means “yes, it describes me perfectly”. This set of questions was extracted from a *Centro de Investigaciones Sociológicas* report (number 3112, December 2015) as a reduced variant of the Schwartz model (Schwartz, 2012) oriented to identify attitudes towards innovation and change.

- *Privacy concerns*. This variable reflects a significant concern about the negative effects of science and technology on the protection of personal data and

privacy. It has been built as a dichotomous variable from the results of the question Q.14.9: “If you had to take stock of science and technology considering all the positive and negative aspects on protection of personal data and privacy, which of the following options would best reflect your opinion? (1) “Harms are greater than the benefits”; (0) “benefits outweigh harms” or “benefits and harms are balanced”.

- *Distrustful towards the appropriate functioning of science and technology.*

This variable was built from question Q18 where the respondents used a scale from 1 to 5, where 1 means that they strongly disagree with the statement and 5 means that they strongly agree with the following statement: “We cannot rely on scientists to tell the truth if they are dependent on private funding”.

Finally, the opposition to robotization in the workplace was included as a predictor of the opposition towards artificial intelligence. This variable was built analogous to the dependent variable, as the subtraction between the valuation of the risks less the valuation of the benefits of the robotization in the workplace. The analyzed phrases are the following: “Using a scale of 1 to 5, where 1 means “no risk” and 5 means “many risks”, to what extent do you think there are risks in the robotization in the workplace?”; “And now considering the benefits and using a scale of 1 to 5, where 1 means “no benefit” and 5 means “many benefits”, to what extent do you think the robotization in the workplace has benefits?”.

## Results

### *Differences among sociodemographic groups*

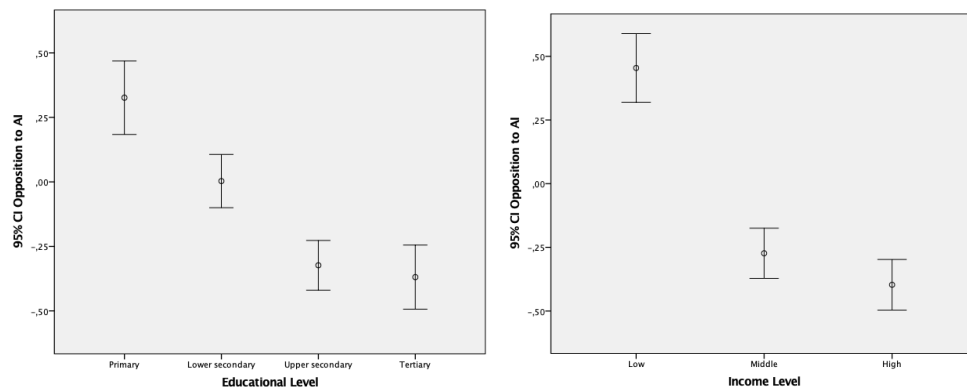
In our case of study, one third of the population (33.3%) believe that AI has more risks than benefits, 38.4% believe that it has more benefits than risks and 28.3% believe that risks and benefits are balanced, on a 11 points scale, between -5 and 5 (See appendices 1-3). The descriptive analysis of the dependent variables crossed by the main demographic variables -gender, age, level of education, household income and rural/urban settings- show small differences among groups. Level of education and household income showed significant (but moderate) differences.

As presented in Fig. 1, individuals with lower educational levels show a slightly higher opposition to AI. On the other hand, as the level of education increases, the weight of the benefits increases in the perception of this technological sector. In a similar sense, individuals in households with lower income levels are slightly more

prone to expressing a critical approach to AI. A theory of competition would expect that lower-skilled workers will perceive a greater competition with technology for jobs, and therefore a greater risk of worsening their working conditions or, even, of losing their jobs since several studies show these workers are (and will be) affected to a greater extent by the disruption these new developments may involve, pointing at a future with fewer lower-skilled jobs available (e.g. Manyika et al., 2017; Frey and Osborne, 2017; Brynjolfsson & McAfee, 2014) and with worse labor conditions (e.g. Spencer, 2018; Fleming, 2017).

Although attitudinal differences by educational level and income are observed these differences are smaller than the competition theory might suggest. We performed a multiple regression analysis to assess to what extent this theory of competition has a high or low explanatory power in explaining the opposition to artificial intelligence.

Figure 1. Opposition to Artificial Intelligence, by educational level



Notes: (1) Values rank between 5 and -5. Positive values mean net opposition. (2) Average net family income in Spain is around 1,100 Euros per month; “high” is considered more than twice that value; “low” is considered less than half that value. (3) ANOVA tests (with Scheffé post hoc test) show that the mean differences between the low-income households and the other two groups are significant at a 0.01 level, as well as the mean differences between the first three groups (primary, lower secondary and upper secondary).

### ***Predicting opposition to artificial intelligence***

We fitted a linear regression model to predict opposition to artificial intelligence, introducing the independent variables in blocks (Table 1). In the first block, we introduced the sociodemographic variables as described in the previous section: gender, age, income, work status, and educational level. In the second block, we introduced the

‘scientific literacy’ variable, considering that it has been the main indicator employed in the literature explaining opposition to new technologies by the cognitive deficit model (Bodmer, 1985; Ziman, 1991). In the third block, we introduced the four variables of values and attitudes as described in the previous section: egalitarianism, privacy concerns, resistance to innovation and distrust in the actual application of science and technology. In the fourth block, we introduced the opposition to robotization in the workplace as a predictor of the opposition towards artificial intelligence. As for collinearity, the tolerance values are close to 1, so there are no problems of collinearity (with values of 0.1 or less). The variance inflation factor (VIF) has low values, around 1, so it confirms the previous results.

Table 1. Linear regression models predicting opposition to artificial intelligence

DV: Balance between risks and benefits of artificial intelligence					
Model	Predictors	Beta	p-value	Tolerance	R <sup>2</sup>
1	(Constant)		0.357		
	Gender	0.071	0.000	0.993	
	Age	0.083	0.000	0.927	
	Income level	-0.115	0.000	0.937	
	Economically active	0.058	0.001	0.925	
	College education	-0.026	0.135	0.930	0.030
2	(Constant)		0.035		
	Gender	0.069	0.000	0.992	
	Age	0.074	0.000	0.915	
	Income level	-0.108	0.000	0.929	
	Economically active	0.061	0.000	0.923	
	College education	-0.012	0.483	0.904	
	Scientific literacy	-0.081	0.000	0.932	0.036
3	(Constant)		0.074		
	Gender	0.067	0.000	0.988	
	Age	0.059	0.001	0.907	
	Income level	-0.103	0.000	0.925	
	Economically active	0.044	0.011	0.899	
	College education	-0.008	0.635	0.898	

	Scientific literacy	-0.078	0.000	0.929	
	Egalitarianism	0.094	0.000	0.949	
	Privacy concerns	0.140	0.000	0.983	
	Resistance to innovation	0.060	0.000	0.986	
	Distrust in Science	0.051	0.002	0.982	0.076
4	(Constant)		0.026		
	Gender	0.027	0.037	0.984	
	Age	0.047	0.001	0.907	
	Income level	-0.044	0.001	0.916	
	Economically active	0.041	0.003	0.899	
	College education	-0.009	0.530	0.898	
	Scientific literacy	-0.024	0.072	0.922	
	Egalitarianism	0.018	0.175	0.935	
	Privacy concerns	0.057	0.000	0.964	
	Resistance to innovation	0.019	0.139	0.982	
	Distrust in Science	0.005	0.715	0.976	
	Opposition to Robotization	0.619	0.000	0.921	0.429

Model 1 shows that sociodemographic indicators (gender, age, income, and work status) have a moderate effect ( $0.021 > R^2 > 0.13$ ), following Cohen's criteria to value the effect size of the adjusted  $R^2$  (Cohen, 1988). Nevertheless, college education shows no significant effect ( $p > .05$ ). Therefore, theories of competition and relative vulnerability (H5) cannot be fully supported; only income level ( $\beta = -.115$ ;  $p = 0.000$ ) and work status ( $\beta = .058$ ;  $p = 0.001$ ) have a significant effect on the perceptions of AI.

Older people and women are significantly more prone to oppose artificial intelligence. The effect produced by age ( $\beta = .083$ ;  $p = 0.000$ ) is arguably linked to the greater reticence to the use of new technologies—and, therefore, to the technological change in the workplace—among older cohorts. As Westerman and Davies (2000: 478) showed, “experiential, physiological, and cognitive factors are identified that place older adults at a disadvantage, relative to younger adults, when using new technologies”. Moreover, gender differences have been observed repeatedly for other controversial technologies, such as nuclear energy (Davidson and Freudenburg, 1996, Sundström and McCright, 2016). As in that case, this gender gap ( $\beta = .071$ ;  $p = 0.000$ ) may

be explained by the different emphasis that socialization gives to security concerns and the perception of risk to men and women (Solomon et al., 1989; Bord and O'Connor, 1997).

In the second block, we included the scientific literacy indicator, slightly improving the goodness of fit of the model ( $R^2=.036$ ). Higher levels of scientific knowledge (H1) are associated with more positive perceptions of AI ( $\beta=-.081$ ;  $p=0.000$ ).

In the third block, indicators of attitudes towards science and values (egalitarianism, privacy concerns, resistance to innovation, distrust in science) increases the goodness of fit of the model ( $R^2 = 0.076$ ), and substantiate some of our hypotheses. In sum, the following hypotheses are supported:

H2: Those with distrustful towards the appropriate functioning of science and technology are more likely to have a more negative perception of AI ( $\beta=.051$ ;  $p=.002$ );

H3: Those less prone to innovation are more likely to have a more negative perception of AI ( $\beta=.060$ ;  $p=.000$ );

H4: Egalitarian worldviews are associated with more negative perceptions of AI ( $\beta=.094$ ;  $p=.000$ );

H6: Those expressing privacy concerns are more likely to have more negative perceptions of AI ( $\beta=.140$ ;  $p=.000$ ).

Finally, in Model 4, we included the balance between risks and benefits of robotization in the workplace to predict opposition to artificial intelligence. This last model reaches a very large effect ( $R^2 = 0.429$ ) and substantiate our last hypothesis (H7). Perceptions of AI are associated with perceptions of robotization in the workplace ( $\beta=.0.619$ ;  $p=.000$ ). Tolerance values do not indicate any problems of collinearity in this model. The Pearson correlation between our indicators of opposition to artificial intelligence and to robotization in the workplace is 0.652 ( $p < 0.001$ ).

## Discussion

In the case of the opposition to artificial intelligence, most sociodemographic indicators (gender, age, income, work status) have a significant but moderate effect; less of 3% of the variance in the dependent variable is explained by the independent variables. Furthermore, the effect of having college education is not significant when controlled by these variables. Our results show that traditional explanations of

opposition to artificial intelligence, such as competition and relative vulnerability theories, have a very moderate explanatory power of views on AI.

Moreover, age differences may be explained by the “experiential, physiological, and cognitive factors” identified by Westerman and Davies (2000: 478) as they place older individuals at a relative disadvantage when using new technologies. Additionally, gender socialization shows a significant but moderate effect on the opposition to artificial intelligence, in the same direction found for other controversial technologies (Sundström & McCright, 2016).

Stronger effects are shown by cultural values and attitudes to science. Those expressing egalitarian (Marris, Langford & O’Riordan, 1998; Carlisle & Smith, 2005) and privacy concerns, as well as those who express less confidence in the actual application of science (Torres-Albero & Lobera, 2017) and those less predisposed to innovation and change, are more prone to oppose both technological applications.

Lastly, we found evidence of a strong correlation between attitudes towards robotization in the workplace and artificial intelligence. This opens the door to new hypotheses that help us explain the formation of attitudes that oppose technological change. The evidence found shows that, beyond the variables associated with established theories, the greatest effect in explaining the opposition to artificial intelligence is in the individual’s opposition to robotization at work. We argue that, as in other controversial applications, cognitive shortcuts take place (Scheufele, Corley, Shih, Dalrymple, & Ho, 2009; Brossard et al., 2009; Ho, Brossard & Scheufele, 2008), in this case between both technological applications: the “intelligent machine” as a new threatening or beneficial element.

A significant part of the population perceives AI and robotization in a similar way, subject to the same conditioning factors. Those more favorable to the emergence of the “intelligent machine” are individuals who trust science, do not distrust the influence of the market on science, show attitudes prone to change and innovation, and have individualist values. On the other side, those who oppose the “intelligent machine” perceive these applications as a continuum, subject to the same risks of being misused by companies, and increasing inequality. In this case, there is a cognitive connection between both technological applications that derives in their common social representation: the “intelligent machine” -or the “smart machine” as coined by Zuboff (1988) decades ago- as a new threatening or beneficial element.



Recent studies show that different cultures exhibit more similarities than differences in attitudes towards robots (Haring, Mougenot, Ono, & Watanabe, 2014; Gnambs & Appel, 2019). This suggests that our findings may apply broadly across cultures. Nevertheless, more research is needed to uncover cultural differences in the factors that influence individual attitudes towards AI.

Discussions on AI and the development of robotics have been common in the public sphere since the post-war years. However, some studies have shown that a number of negative concerns have emerged in the last decade (Fast and Horwitz, 2017). This represents a challenge for both the private and public sector. In the case of the former, forecasts about the threatening impact of AI by both media and certain experts might influence the introduction of these new technologies, leading to distrust or even rejection by users. This also implies the necessity of a growing relationship between AI and PR departments in corporations.

Design and PR departments must come up with new ideas to engage users and overcome those fears with new strategies, such as involving the user to help with the acceptance of “intelligent machines” in social life (Reich-Stiebert, Eyssel and Hohnemann, 2019), or working with the public on other collaborative actions (Brunton and Galloway, 2016). This might not be an easy issue, as PR departments might have underperformed in their communication strategies, acting as “AI cheerleaders” (see Bourne, 2019) and hence obscuring broader perspectives on AI (Galloway and Swiatek, 2018). Regarding the public space, some authors state that it is important to frame a strong public debate about the implications of these emerging technologies to help promote and maintain a public agora (Echevarría and Tabarés, 2017) and to engage and inform the public about the implications of AI.

## **Conclusions**

Despite AI becoming more prevalent in the public debate, little is known about what factors might structure people’s attitudes towards this technology. In this study, our aim has been to investigate, for the first time, such factors through the analysis of data from a survey in Spain. We show that common explanations of opposition to artificial intelligence, such as competition and relative vulnerability theories, have a small effect size. Those potentially more affected by the advance of automatization — i.e. lower-skilled workers (Manyika et al., 2017; Frey and Osborne, 2017)— do not oppose artificial intelligence to a significantly greater extent. Similarly, the public

understanding of science model shows a moderate explanatory effect, as observed in other cases (Mielby et al., 2013; Torres-Albero & Lobera, 2017).

Cultural values and attitudes to science offer a more effective explanation of this opposition than competition theories: those expressing egalitarian values and privacy concerns are more likely to oppose artificial intelligence, as well as those who express less confidence in the actual application of science and those less predisposed to innovation and change. These results bring to the fore the ongoing issue over who is debating the emergence of AI, and the need for inclusive policies that should be promoted through effective communication from PR departments (Galloway and Swiatek, 2018).

Finally, we found a strong connection between attitudes towards robotization in the workplace and towards artificial intelligence. We argue that a common social representation, the “intelligent machine,” emerges as a new threatening or beneficial element. Certainly, some influential literature in which AI and robotics appear deeply intertwined may have helped to blur the differences, and hence, AI are described as smart machines (Zuboff, 1988). However, AI’s much broader than just robots, and highlighting the differences remains a pending task for corporations, experts and governments (Galloway and Swiatek, 2018).

The implications of these results are therefore significant for communication in both the artificial intelligence sector of and the robotization sector. These are two distinct sectors; yet, we show that they are strongly connected at the attitudinal level among the public. A first implication is that if there are changes (positive or negative) that impact the public perception of one of the sectors, our prediction is that these changes will be transferred to the perception of the other. The public communication of these sectors must consider that attitudes (favorable or unfavorable) are currently built on an undifferentiated perception: the “intelligent machine” that benefits —or threatens. Furthermore, as mentioned before, this effort should not only involve both sectors, but governments and experts alike.

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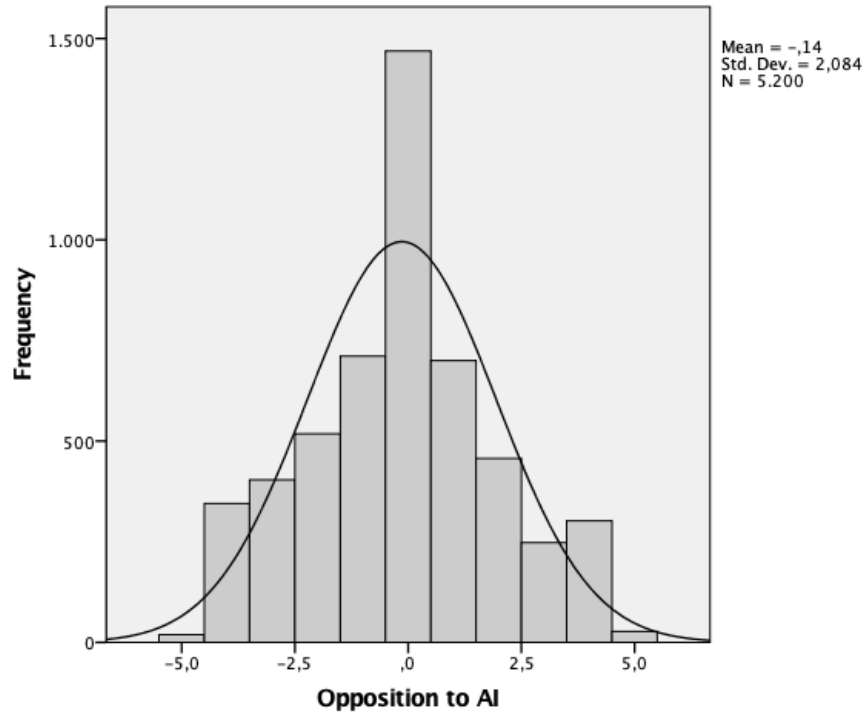
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## Appendices

### Appendix 1. Histogram of the distribution (opposition to artificial intelligence).



### Appendix 2. Distribution of frequencies and percentages (opposition to artificial intelligence).

	Frequency	Percent	Cumulative Percent
-5: All benefits, no risk	19	.4	.4
-4	345	6.6	7.0
-3	404	7.8	14.8
-2	518	10.0	24.7
-1	711	13.7	38.4
0: Risks and benefits are balanced	1469	28.3	66.7
1	700	13.5	80.1
2	457	8.8	88.9
3	248	4.8	93.7
4	302	5.8	99.5
5: All risks, no benefit	27	.5	100.0
Total	5200	100.0	

### Appendix 3. Basic statistics of the distribution (opposition to artificial intelligence).

N	5200
Mean	-.14
Std. Error of Mean	.029
Std. Deviation	2.084
Variance	4.343
Skewness	.066
Std. Error of Skewness	.034
Kurtosis	-.314
Std. Error of Kurtosis	.068

## Appendix 4.

Variable	Categories	Descriptive statistics
<i>Sociodemographic factors</i>		
Gender	0=Men 1=Women	51.4% Women
Age	Age (in years)	M= 43.95, SD=17.951
College education	0= Without college education 1= With college education	21% with college education
Work status	0= Economically inactive 1= Economically active	% 56.6 Economically active
Household's family income	1= Much higher (more than 2,200 Euros per month) 2= Higher 3= Around 1,100 Euros per month 4= Lower 5= Much lower (less than 550 per month)	M=2.78, SD=0.910
<i>Scientific knowledge (deficit model)</i>		
Scientific knowledge	Number of correct answers (See Q24 in the questionnaire at <a href="https://icono.fecyt.es">https://icono.fecyt.es</a> ). Scale from 0 (= none correct) to 6 (= all correct)	M= 4.24, SD=1.220
<i>Values</i>		
Egalitarianism	Scale from 1 (=The state must give more freedom to business / corporations) to 10 (=The state must control companies more effectively)	M= 6.11, SD=2.933



Privacy concerns	0= "Benefits outweigh harms" or "benefits and harms are balanced" 1= "Harms are greater than the benefits"	34.3 % states that harms are greater than the benefits
Distrustful towards the appropriate functioning of S&T	Scale from 1 (= Strongly disagree) to 5 (=Strongly agree)	M= 3.25, SD=1.152
Resistance to innovation	Factor from Q29.1 to Q29.6 (See questionnaire). From -3.805 to 3.0417	M= 0, SD=1 Cronbach's Alpha = 0,772
Opposition to Robotization	Scale from -5 (= no risk, many benefits) a 5 (= many risks, no benefit)	M= 0.12, SD= 2.166