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TIPO: Aplicación

Does the Image that the Population Has of Robots Influence the Perception of the Impact of Automatization on Employment?

¿Influye la Imagen que la Población Tiene de los Robots en la Percepción del Impacto de la Automatización en el Empleo?
A Imagem que a População Tem dos Robôs Influencia a Percepção do Impacto da Automatização no Emprego?

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The image that people have of robots/AI often does not correspond to reality. This can have effects on the effective implementation of these technologies in a country, generating a negative impact on its competitiveness. The objective of this article is to analyze whether the idea one has of a robot influences the perception of the impact of robotization on employment. To do this, partially based on the research of Shoss and Ciarlante (2022), it is employed a multilevel model with variables at the individual and country levels, incorporating to study, as a contribution, the density of robots per country as an independent variable into the study. The results confirm that: (i) the more distorted the image an individual has of what a robot is (Wrong image), the greater their perception that robots/AI pose a threat to jobs; and (ii) that in those countries where the density of robots is higher (operating robots per 10.000 workers), this perceived threat level is lower.

La imagen que las personas tienen de los robots/IA en muchas ocasiones no se corresponde con la realidad. Esto puede afectar a la implantación efectiva de estas tecnologías en un país, generando un impacto negativo sobre su competitividad. El objetivo del presente artículo es analizar si la idea que se tiene de un robot influye en la percepción del impacto de la robotización en el empleo. Para ello, partiendo parcialmente en la investigación de Shoss y Ciarlante (2022), se utiliza un modelo multinivel con variables a nivel individual y de país, incorporando al estudio, como aportación, la densidad de robots por país como variable independiente. Los resultados confirman que: (i) cuanto más distorsionada es la imagen que un individuo tiene sobre lo que es un robot (Imagen errónea) mayor es su percepción de los robots/IA como amenaza para los empleos; y (ii) que en aquellos países donde la densidad de robots es mayor (robots operativos por cada 10.000 trabajadores), este nivel de amenaza percibida es menor.

A imagem que as pessoas têm dos robôs/IA muitas vezes não corresponde à realidade. Isso pode ter efeitos na implementação eficaz dessas tecnologias em um país, gerando um impacto negativo em sua competitividade. O objetivo deste artigo é analisar se a ideia que se tem de um robô influencia na percepção do impacto da robotização no emprego. Para isso, baseando-se parcialmente na pesquisa de Shoss e Ciarlante (2022), utiliza-se um modelo multinível com variáveis individuais e de país, incorporando ao estudo, como contribuição, a densidade de robôs por país como variável independente. Os resultados confirmam que: (i) quanto mais distorcida é a imagem que um indivíduo tem do que é um robô (Imagem errônea), maior é sua percepção dos robôs/IA como uma ameaça aos empregos; e (ii) que nos países onde a densidade de robôs é maior (Robôs operacionais por cada 10000 trabalhadores), este nível de ameaça percebida é menor.

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1. Introduction

There is currently a debate about how the growth of automation based on robots/AI affects employment and the competitiveness of countries and companies. While initial contributions highlighted adverse effects on employment, the increase in the use of these technologies in terms of quantity and capabilities brings new results, making it necessary to contrast these conclusions. In any case, the fear of being replaced by a robot in the workplace, known as automation anxiety, is real; and far from being exclusive to our time, it is a cyclical phenomenon (Bassett and Roberts 2019) that periodically emerges in public debate, impacting the transformation process linked to the implementation of these technologies. From this perspective, it becomes relevant to study how society perceives automation, particularly robots, and how it perceives the risk (threat) to employment.

The literature includes various studies on the impact of automation on employment. The traditional view presents it as a threat. Frey and Osborne (2017) study the probability of computerization for 702 occupations and the expected impacts in the US, identifying the number of jobs at risk and the relationship between the probability of computerization of an occupation, wages, and the educational level. Acemoglu and Restrepo (2020a) corroborate these results and highlight the strong negative effects of robots on employment and wages in the areas where this substitution occurs. More recently, considering the advent of generative AI, Felten et al. (2023) studied the effect of this disruptive technology on more than 800 occupations, identifying a greater threat in "white-collar" jobs (high education and good wages).

In contrast, studies are beginning to find a significant positive relationship (opportunity or positive risk) between automation and employment (Klenert et al., 2023). Both in this work and in Antón et al (2022 and 2023), the positive effect of high automation in countries across Europe is concluded; and unlike some previous studies, they do not find evidence of a reduction in the proportion of low-skilled workers. On the other hand, it is necessary to incorporate practical considerations of industrial reality that condition automation and, therefore, necessarily limit its effects. Fernández-Macias et al. (2021) argue that contrary to popular belief, the types of robots used in manufacturing today do not imply a discontinuity in terms of automation and labor replacement possibilities, practically limiting the current potential impact of robotization on employment.

Greater proactivity in adapting to automation can leverage this opportunity, generating a net increase in employment that compensates for possible losses due to substituting human tasks. Countries and companies must face this challenge and continue to grow in competitiveness sustainably. Arntz et al. (2016) note that although automation will replace certain workers, they can adapt by changing tasks, thus avoiding technological unemployment. Furthermore, the promoted development will generate jobs through demand linked to new technologies and the positive effect of increased competitiveness itself. López-Sánchez et al. (2019) delve into job creation and the need to train and re-skill workers, observing greater job creation than destruction and how countries with high automation present higher levels of competitiveness. Acemoglu and Restrepo (2022a) analyze productivity improvement linked to the growth of automation in four countries with the highest robot density per worker (Japan, Germany, South Korea, and the US) as a response to the aging problem leading to a shortage of middle-aged specialized workers.

Keywords
Robotization, Artificial Intelligence, threat perception; Image of the robots. Eurobarometer.

Palabras clave
Robotización; Inteligencia artificial; percepción de amenaza; Imagen de los robots. Eurobarómetro.

Palavras-chave
Robotização; Inteligência artificial; percepção de ameaça; Imagem de robôs. Eurobarómetro.

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O14, O33, Q55

The perception of technology, positive or negative, in general terms, plays a relevant role in this transformation process driven by automation, which is not only industrial but fundamentally social. In this perception, two elements can be distinguished: (i) the image people have of robots/AI and (ii) the perceived level of risk (threat). These are two different but linked elements: if the image changes, a modification of the threat level is expected. The perception, thus understood, is linked to individuals' behavior and the acceptance or rejection of technology. Thus, for Carradore (2022), only individual (sociodemographic) factors and the technology acceptance model (TAM) influence attitudes toward robots for their acceptance by end users. For Turja and Oksanen (2019), personal experiences with robots at work or elsewhere are associated with greater acceptance, with a greater effect at the individual level than at the country level. Budeanu et al (2023) identify the specificity of national structures and cultures, that shape individual thoughts, as the most significant factors in the perception of AI's future impact on people, giving less relevance to sociodemographic variables. Shoss and Ciarlante (2022) incorporate the reference to a country's inequality into their analysis of the perception of robots/AI. Taking the Gini index as a measure, they find that the perception of employment threat is greater in countries with higher inequality.

Interaction or exposure to technology necessarily affects people's perception of it. Therefore, it is relevant to introduce variables in studies and models that provide information about the penetration of technologies in the studied areas or countries. Specifically, in the present work, "robot density" in each country, calculated as the number of robots per 10,000 workers, has been incorporated as a variable to characterize the level of robot implementation. In this formulation, it is of great interest to the research since it is a variable that relates robots and employment. Additionally, it contributes to the analysis of perception as an objective, quantifiable variable widely used in the literature that studies robots and their impact at the country level. The use of this variable is a contribution of this work since it has not been previously used in similar studies.

The present research aims to delve into the study of the perception of robots as a threat to employment, considering its relationship with the image of robots and the level of their implementation in a country. The following section details the theoretical framework that underpins the two hypotheses structuring the work. Next, the research methodology is identified, defining the materials and methods, followed by a discussion of the results. Finally, the conclusions, limitations, and future lines of research are addressed.

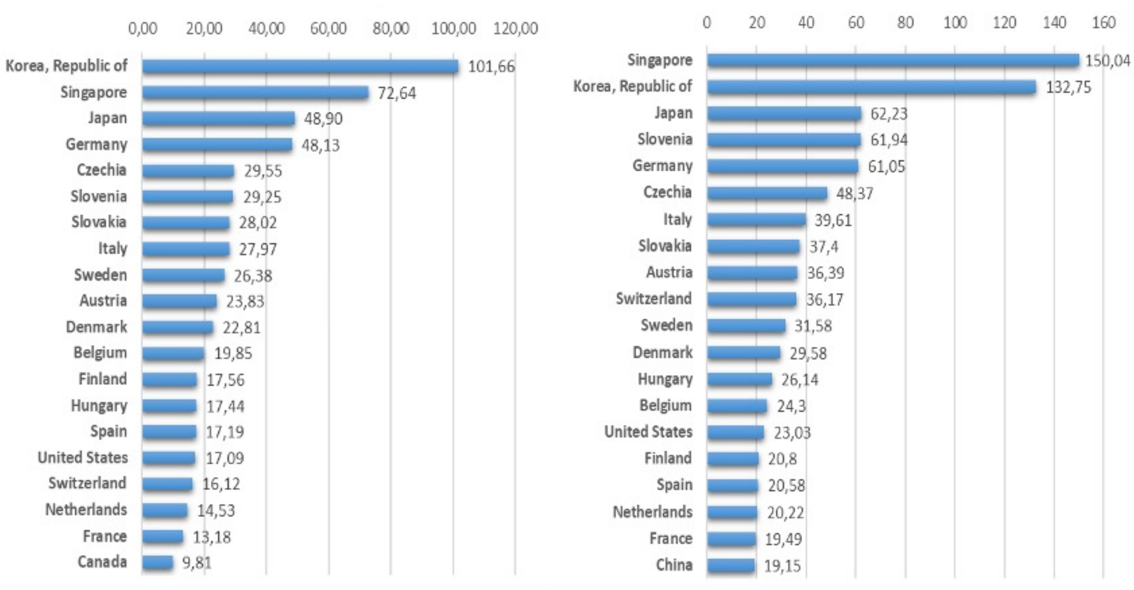
2. Theoretical Framework

2.1. Robot Density and Its Effects. Hypothesis 1

The number of robots is clearly a point of interest not only for measuring automation but also as a measure of AI implementation (Liu et al. 2020; Li et al. 2023; Shen and Zhang 2024; Wang et al. 2024). The adoption of robots in the most developed countries is ongoing and evident. **Figure 1** shows the significant increase in robot density between 2017 and 2022 for the 20 countries with the highest density, considering the total employed population (Source: International Labour Organization, ILO, 2024). These

20 countries present high levels of welfare and competitiveness, as well as human development, allowing for a preliminary deduction that the intensity of automation is not at odds with competitiveness and does not necessarily imply job loss.

Figure 1 - Ranking of 20 countries with the highest robot density per 10,000 workers in: a) 2017 and b) 2022.



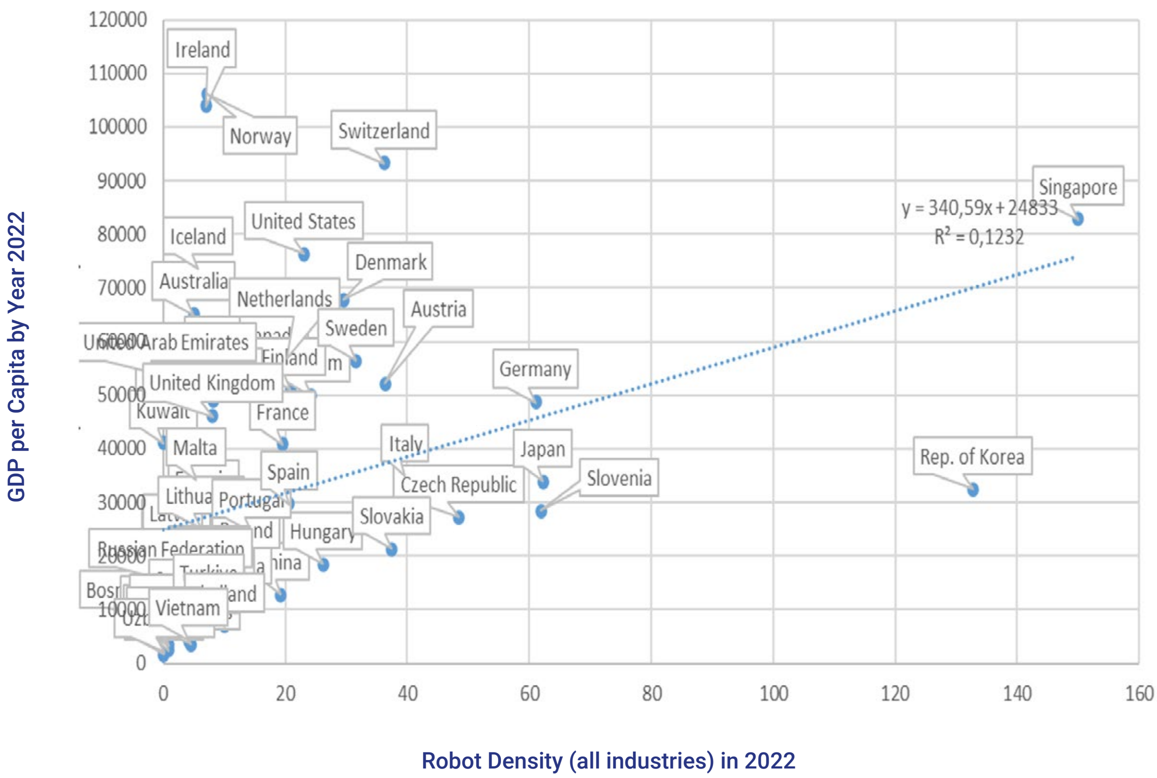
a) 2017 b) 2022

To complete the description of the global scenario, the relationship between the reference variable (robot density) and global country indices, in this case, GDP per capita, has been analyzed. In **Figure 2**, based on data from the International Labour Organization (ILO, 2024) and economic data from the World Bank, it can be observed that robot density (number per 10,000 workers) is positively correlated with GDP per capita (current US$ prices).

However, analyzing variables associated with the number of robots, such as density or stock, is also very useful in highlighting the positive externalities of robotization on employment, technological innovation, sustainability, and export performance.

In relation to employment, various studies have explored the impact of robotization on aspects such as employment, wages, and labor productivity. Battisti and Gravina (2021) observed greater complementarity between robots and older workers (hours worked by employees aged 50 and over), and greater substitutability with younger workers. On the other hand, Compagnucci et al. (2019) indicated that a 1% increase in the number of robots reduces the number of hours worked by 0.16%, also affecting sale prices and real wages. Klenner et al. (2023) investigated the relationship between robot adoption and employment in Europe, using industry-level data, concluding that the use of robots is linked to an increase in aggregate employment. Additionally, Shen and Zhang (2024) noted that incorporating artificial intelligence (AI) through industrial robots in Chinese companies has increased the number of jobs. These authors argue that the increase in labor productivity and the evolution in the division of labor due to robotics have compensated for the potential negative impacts of this technology on employment.

Figure 2 - GDP per Capita by Year and Robot Density in 2022. Own elaboration based on World Bank, IFR, and ILO data.



From the perspective of innovation, Liu et al. (2020) examined how AI fosters technological innovation in 14 manufacturing sectors in China, highlighting that AI enhances the creation and dissemination of knowledge, improves learning and absorption capabilities, and increases investment in R&D and talent. This effect is more pronounced in low-tech sectors and intensifies with higher levels of AI. On the other hand, Wang et al. (2024) suggest that AI transforms human capital, innovation patterns, and the market environment, improving innovation efficiency. Luo and Qiao (2023) add that adopting industrial robots can boost high-quality innovation, indicating that an increase of one robot per 100 employees is associated with a 13.52% increase in invention patent applications the following year. In summary, there seems to be empirical evidence that industrial robots promote business innovation by attracting more educated workers and dedicating more employees to R&D activities.

Regarding sustainability, research advancements highlight how this development contributes to its improvement. Yu et al. (2023) explore the effect of industrial robots on carbon emissions using city-level data. Their findings show that implementing industrial robots has significantly reduced city carbon emissions, aiding decarbonization by improving energy efficiency and adopting green technology. Similarly, Li et al. (2023) provide empirical evidence of the positive impact of artificial intelligence on improving energy efficiency and resource use in Chinese companies.

Finally, regarding the export capacity of companies, Zhang et al. (2023) highlight how the implementation of robots in companies leads to improvements in export capacity. These authors observe that companies not only increase the likelihood of exporting but also improve their export performance due to the reduction of variable production costs and access to a broader international customer base. However, they identify significant differences between large companies and SMEs. While for large corporations, the integration of robots translates into a competitive advantage in exports and an increase in market share, SMEs do not seem to obtain these benefits, suggesting that the effects of robotization can vary considerably depending on the company's size.

Therefore, there seems to be some empirical evidence that increasing robot density generates benefits at various levels (employment, technological innovation, sustainability, and export behavior). It thus seems reasonable to expect that in countries with high robot density, the perception of robots will be more positive. This leads us to formulate the first research hypothesis:

> *Hypothesis 1: The higher the robot density in a country, the more positive the perception of robots will be (perception of less employment threat or lower perceived risk level).*

2.2. Robots/AI and Perception. Hypothesis 2

Personal behavior, whether acceptance or rejection (non-acceptance), is key to the success of technologies. In this sense, acceptance goes hand in hand with perception, implying that the extent to which technologies can benefit society depends on how they are perceived. A key aspect of the perception of robots seems to be the experience with this technology at work. Turja and Oksanen (2019), analyzing robot acceptance at work (RAW) with individual and national attributes in the EU 27 (Eurobarometer), find that experiences with robots at work or elsewhere are associated with higher acceptance. The physical form of robots also seems to influence perception (Geiselmann et al., 2023; Bhuiyan et al., 2024), although some studies suggest that the effect depends on the type of activity the robot performs (Della Corte et al., 2023). Similarly, the congruence between function and appearance also plays an important role in acceptance: Kim et al. (2023) conclude that consumers are more inclined to use a robot designed to provide hedonic benefits when it resembles real-life objects, and more inclined to use a robot/AI designed for utilitarian benefits when it has a machine-like appearance.

In conclusion, it can be inferred that the image one has of robots can play an important role in their acceptance, which is reflected in the second research hypothesis of this work:

> *Hypothesis 2: The more distorted and unrealistic the idea of a robot, the more negative the perception of them (perception of greater employment threat or higher perceived risk level).*

3. Materials and Methods

This work partially replicates the research of Shoss and Ciarlante (2022), opting to use the same database utilized by these authors, the Eurobarometer 87.1 (2017), as well as their methodological approach, a multilevel model with individual-level and country-level variables. The data from Eurobarometer 87.1 were collected through interviews conducted in early 2017, considering a representative sample of European citizens aged 15 and over.

The dependent variable defined by Shoss and Ciarlante (2022) is the perception of robots/AI as a threat to employment (PRb_AEm). This variable is calculated as the average value obtained from two Eurobarometer questions, with higher scores indicating a greater PRb_AEm:

To what extent you agree or disagree with each of the following statements:

1) *Due to the use of robots and artificial intelligence, more jobs will disappear than new jobs will be created; and*
2) *Robots and artificial intelligence steal people's jobs.*

Regarding the individual-level variables (**Table 1**), those used by Shoss and Ciarlante (2022, p. 10) have been considered, using the same measurement scale for all of them, and additionally incorporating the variable " Incorrect image of robots."

Table 1. - Individual-level variables

Variable	*Description*
Gender	Dichotomous, "Female" is the base level in the model
Age	Numeric, age of the individual.
Community	Categorical: 1 (rural area or village), 2 (small or middle-sized town), 3 (large town).
Education	Numeric, age at which the individual stopped full-time education.
Political orientation	Numeric, individual's ideological orientation on a scale from 1 (left) to 10 (right).
Technological skills	Numeric, self-perception of skills in using digital technologies on a scale from 1 to 4.
Future technological skills	Numeric, self-perception of skills in using digital technologies in a future job on a scale from 1 to 4.
Job performed by robots in the future	Numeric, opinion on whether a robot or AI could perform the respondent's current job in the future, on a scale from 1 to 4.
Reading	Dichotomous, YES/NO the respondent has read, seen, or heard anything about artificial intelligence in the last 12 months. “NO” is the base level in the model.
Use of robots (work)	Dichotomous, YES/NO the respondent currently uses any type of robot at work. “NO” is the base level in the model.
Future social inequality	Numeric, respondent's opinion on whether social inequality in their country will be less or more than at present, on a scale from 1 to 5.
Incorrect image of robots	Numeric, match between the shown image and the respondent's image of what a robot is, on a decreasing scale from 1 to 4.

Regarding the variable "Incorrect image of robots," a question from the Eurobarometer was used that, when presented with the image of an industrial robot (**Figure 3**), asked respondents to indicate whether this image corresponded little (high scores) or much (low scores) with their image of what a robot is.

Figure 3 - Image of a robot associated with question QD7_1 of Eurobarometer 87.1

Source: TNS Opinion & Social: Special Eurobarometer 460 / Wave 87.1

However, at the country level, instead of using the GINI index, the human inequality coefficient, or the logarithm of GDP per capita, as the aforementioned authors do, robot density (operational robots per 10,000 active population) has been used. The data for calculating this variable were obtained from the International Federation of Robotics, IFR (2023) (robot stock in 2016) and the World Bank (active population in 2016). In this regard, it should be noted that there is no information on robot density for Luxembourg and Cyprus, so only 26 countries were considered, instead of the 28 used in the original work of Shoss and Ciarlante (2022).

Thus, after removing incomplete records from the various databases used, the final sample used in the model consists of 8,778 individuals, of whom 49.5% are women.

All the analysis was carried out in R (R Core Team, 2013), using the packages "haven" (Wickham et al., 2023), "dplyr" (Wickham et al., 2021), "lmerTest" (Kuznetsova et al., 2017) and "lme4" (Bates et al., 2015).

4. Results and Discussion

The results of the multilevel model are shown in **Table 2**. Even though the sample is not exactly the same as that used by Shoss and Ciarlante (2022, p. 10) for the aforementioned reasons, it is observed that the results for the common variables in both studies are virtually identical.

Since the dependent variable considered, PRb_AEm, represents the level of agreement that AI/robots threaten jobs, positive signs in the coefficients imply an effect of increasing the perception of threat. Based on the results obtained, it is observed that men consider the threat to jobs lower than women (Gender). As the size of the habitat (Community) and the years of education (Education) increase, the perception of threat decreases. As noted by Torrent-Sellens et al. (2021) regarding trust in surgical robots, it is confirmed that the perception is more positive in individuals with higher educational levels.

Similarly, higher current and future perceived technological skills reduce the fear of the threat posed by robotization. This is consistent with the results of Novozhilova et al. (2024), who concluded that individuals with a higher perception of technological competence felt more comfortable with AI. Having read, heard, or seen something about AI in the last 12 months (Reading) and using robots at work (Use of robots - work) also reduce the fear of robotization. This result is consistent with that of Turja and Oksanen (2019), whose conclusions pointed out that experiences with robots at work or elsewhere are associated with higher acceptance levels. Conversely, as the assessment of whether a robot or AI could perform the respondent's current job in the future increases, so does the perception of risk. The same happens with the opinion on future social inequality: the greater the predicted inequality, the higher the risk perception. Finally, neither age nor political orientation seems to affect the dependent variable.

Regarding the two variables of interest in this study, both are significant and have the expected sign. On the one hand, it is confirmed that the more distorted an individual's image of what a robot is (incorrect image), the greater their perception that robots/AI pose a threat to jobs. Thus, hypothesis 2 is confirmed. The fact that two other variables closely related to the real knowledge of what a robot is (Reading and Use of robots - work) are also significant and have a negative sign reinforces this conclusion. It seems that those individuals with a lower understanding of what a real robot is are precisely the ones who perceive a greater threat. On the contrary, those who are better informed because they have read, heard, or seen something about AI in the last 12 months, work with robots, and/or know what they really look like, perceive a lower threat level.

Regarding hypothesis 1, it is apparently confirmed: the higher the robot density in a country (stock of operational robots), the more positive the perception of them is (less employment threat). However, it is necessary to clarify that the p-value associated with this variable is 0.024. Although the variable is significant at 5%, a standard in social sciences, we consider it insufficient to unequivocally affirm the hypothesis. Benjamin et al. (2018, p. 6), in their well-known work on statistical significance, recommended "to change the default P-value threshold for statistical significance for claims of new discoveries from 0.05 to 0.005," to improve the replicability of academic research. Following this recommendation, we will therefore limit ourselves to stating that there are certain indications of this possible relationship, and further studies are necessary to confirm or refute it.

Table 2. - Results of the multilevel model.

Variables	Coefficient	SD	P-value
Level 1			
Intercept	3,43	0,10	0,000 ***
Gender (Male)	-0,08	0,02	0,000 ***
Age	0,00	0,00	0,889
Community	-0,04	0,01	0,000 ***
Education	-0,01	0,00	0,000 ***
Political orientation	0,00	0,00	0,307
Technological skills	-0,03	0,01	0,039 *
Technological skills (future job)	-0,04	0,01	0,004 **
Job performed by robots in the future	0,04	0,01	0,000 ***
Reading	-0,13	0,02	0,000 ***
Use of robots (work)	-0,10	0,03	0,001
Future social inequality	0,06	0,01	0,000 ***
Incorrect image	0,04	0,01	0,000 ***
Level 2			
Stock of operational robots	-0,01	0,00	0,024 *
Variance of the intercept	0,037		

Source: Own elaboration.
* P-value < .05. ** P-value < .01. *** P-value < .001.

5. Conclusions, Limitations, and Future Research Lines

People's perception of automation based on robots/AI emerges as key to understanding and modulating the social impact induced by this technology, especially in terms of job creation. Increasing its social acceptance involves reducing the perceived threat, which should enhance the willingness to implement active national policies aimed at leveraging the opportunities presented by the technology, exploiting the scenarios of increased competitiveness and employment that, according to the data, are emerging.

From this point of view, it is worth asking whether, to preserve net employment in the medium term, there really is an alternative to investing in advanced automation technologies. Such investment, in any case, must include the effort to retrain people, not only to work in new positions but to create them. In light of the data, it is not dismissible that a conservative attitude—refraining from implementing technology to avoid short-term job losses—could ultimately lead to net employment losses as a result of a significant reduction in competitiveness compared to countries and companies that do choose to invest.

The line of work presented in this article delves into the use of relevant variables for controlling the impact of automation on employment, which, combined with the proposed methodology, can be very useful as support for the work of policymakers. Having ways to independently measure the two elements that make up perception (the accurate image of technology and the perception of employment threat) facilitates the design of more precise policies aimed at improving each of these elements. With the proposed variables, it is possible to define measurable objectives and monitor the evolution of the impact accordingly. Especially interesting could be the development of public plans to bring robots/AI closer to society.

This work presents several limitations, which in turn open up possible future lines of research. Firstly, it shares the limitations of the work by Shoss and Ciarlante (2022): Eurobarometer countries, currently employed individuals (in order to use the variable of technological skill in the current job), and the inability to confirm specific causality of the different variables. In this regard, it has already been indicated that hypothesis 2 is not considered fully proven. In the future, it would be possible to delve deeper into the research by expanding the sample of countries considered to further test the obtained result.

It is also relevant to qualify the consideration of the timing when the data were obtained. The results should be interpreted in the context prior to the advent of Large Language Models (LLMs) like ChatGPT. The emergence of this technology at the end of 2022 marks a turning point, also in the perception of AI and automation. While this work, like previous studies, seems to confirm that workers with lower educational levels are the ones who show the greatest fear of robotization, the appearance of LLMs represents a disruptive change. In this new scenario, "white-collar" jobs are likely to face greater uncertainty. For this reason, it would not be surprising if this same study conducted with 2024 data yielded very different results in some of the variables considered. In this sense, we believe that the present work can serve as a comparison for future research, making it possible to evaluate how the perception of robotization/AI has changed following the advent of LLMs.

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