



Fear of Robots among European Workers: The Interplay of Cultural and Economic Conditions

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Abstract

The increasing adoption of automation and robotics has sparked widespread concerns among European workers regarding job security. This study explores how cultural and economic conditions shape the fear of robots in the workplace, addressing a gap in existing literature that often focuses solely on economic factors. Using data from the Eurobarometer 87.1 survey (2017), this research employs a multilevel regression analysis to examine the interplay between cultural dimensions, such as uncertainty avoidance, individualism, power distance, and masculinity, and economic indicators, including GDP growth and unemployment rates.

The findings suggest that economic downturns amplify workers' fear of automation, particularly in cultures characterized by high uncertainty avoidance, high individualism, and high indulgence. Additionally, long-term-oriented, and masculine cultures exhibit lower levels of fear, whereas short-term-oriented and feminine cultures show heightened apprehension toward workplace automation. At the individual level, higher educational attainment, managerial roles, and prior experience with automation significantly reduce fear, highlighting the importance of exposure and skill adaptation in mitigating anxieties about technological change.

These results have practical implications for policymakers and businesses seeking to manage workforce transitions in the digital era. Strategies that emphasize lifelong learning, reskilling initiatives, and transparent automation policies can help alleviate workers' fears and promote a more adaptive labor market. Future research should explore longitudinal data and industry-specific variations to further refine strategies for integrating automation into the workplace effectively.

Key words: fear of robots, workplace automation, cultural dimensions, economic conditions, job security, technological anxiety

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1. Introduction

Since the 17th and 18th centuries, technological progress has been a key driver of economic and social transformation in European societies. Each wave of innovation, starting with mechanization during the Industrial Revolution, has led to debates over the impact of technology on employment, job displacement, and social stability (Šmihula 2010). The current wave of technological innovation, known as the Information Age, includes digital technologies such as desktop computing, the Internet, bio- and nanotechnologies and robotics (Dekker, Salomons et al. 2017). These advancements, while driving economic growth and productivity, have also heightened fears about job insecurity. Public discussion reflects these concerns, with media headlines such as “What happens to society when robots replace workers?” (Davidow and Malone 2014), emphasizing anxieties over the future of work.

The fear of automation displacing jobs is not new. Already in 1930 Keynes argued that technological unemployment would result from the rapid pace of labor-saving innovations outstripping the creation of new labor opportunities (Keynes 1930). Recent technological advancements, including artificial intelligence (AI), machine learning, and robotics, have brought even more attention to this issue. A recent study estimated that 14% of EU employees currently work in highly automatable jobs, while an additional 40% face significant changes to their work due to automation (Pouliakas 2018). As the pace of automation accelerates, these concerns are becoming more widespread, with industries across Europe seeing record robot installations in recent years. For instance, in 2021, robot installations reached a record high, increasing by 31% to 517.000 installed units. Given current trends and forecasts, the installation of industrial robots is expected to continue growing in the coming years (Jurkat, Klump et al. 2022).

Considering these developments, workers’ perceptions of automation are critical. As automation transforms industries, some jobs may disappear, while others will undergo significant change (Kozak, Kozak et al. 2020). Fear and suspicion toward automation are already evident, particularly in media reports and public discussion (Davidow and Malone 2014). Workers’ anxieties result from concerns about job displacement and the broader impact of automation on job stability. These concerns are echoed across Europe, with recent studies documenting widespread fears of job displacement by robots (Dodel and Mesch 2020). Moreover, automation’s rapid pace adds complexity to these fears, particularly for workers who are less familiar with new technologies (McClure 2018).

This study aims to explore how cultural and economic conditions interact to influence the fear of workplace automation among European workers. While previous studies have examined the economic impact of automation, few have comprehensively explored the role of cultural factors in shaping workers' attitudes toward technological change (Dekker, Salomons et al. 2017). Cultural conditions, as defined by Hofstede (2001), refer to “*the collective programming of the mind that distinguishes the members of one group or category from another*”. In this definition the “mind” stands for thinking, feeling, and acting, with consequences for beliefs, attitudes, and skills (Hofstede 2001). These cultural factors can shape how workers perceive automation and its implications for their job security. Therefore, the following **research question** will be addressed: *To what extent do cultural conditions interact with economic conditions to influence the fear of robots at work among European workers?*

Exploring the interaction between cultural conditions and economic conditions is academically relevant for various reasons. Firstly, it addresses a gap in the existing literature by integrating cultural conditions and cultural conditions to understand attitudes toward workplace automation among European workers. While previous studies have explored the potential influence of cultural factors on the fear of robots, they have predominantly focused on economic self-interest and uncertainty avoidance (Dekker, Salomons et al. 2017). Therefore, this study aims to conduct a more comprehensive examination of additional cultural factors. Moreover, earlier research has examined fear of robots from either a cultural or psychological standpoint, whereas this study investigates the interaction between these dimensions to provide a holistic view (Dodel and Mesch 2020). Furthermore, the findings of this study will contribute to the fields of human-robot interaction by offering empirical evidence on how cultural dimensions and economic conditions collectively shape the fear of robots.

This interdisciplinary approach examining the effect of cultural dimensions and economic conditions on the fear of workplace automation not only enhances theoretical frameworks but also provides practical insights for employers and policymakers aiming to facilitate smoother transitions to automated workplaces. Given the ongoing digital transformation across Europe, understanding these dynamics is essential for developing culturally sensitive and psychologically informed strategies to address workers' fears, thereby promoting a more inclusive and adaptive workforce.

This thesis is structured as follows: first, the theoretical framework is developed to underpin later analysis. Following this, the dataset and methodology are introduced, detailing

the data used and the approach employed for analysis. The results of the hypothesis tests are then presented, followed by a discussion of the practical and theoretical implications of the findings. Finally, the conclusion addresses the limitations of this research, and offers recommendations for future research.

2. Theoretical Perspectives on Fear of Robots in the Workplace

This study aims to investigate how cultural and economic conditions interact to influence the fear of robots in the workplace. To address this, it is essential to define key concepts and theoretical assumptions that will guide the analysis. In doing so, this section will outline the central concepts: fear of robots in the workplace (Section 2.1), cultural conditions (Section 2.2.1), and economic conditions (Section 2.2.2). Following these definitions, the theoretical interplay between these factors will be explored, and hypothesis will be proposed (Section 2.2.3). Additionally, some control variables will be included that may affect workers' fear of robots (Section 2.3).

2.1 Fear of Robots in the Workplace

The current wave of technological innovation, the information age, is characterized by rapid increases in technology, and the adaptation of cyber-physical systems. As a result of these rapid technological changes, there is a growing concern about their potential impact on employment opportunities and job displacement (Tiwari 2023).

According to a study by the McKinsey Global Institute, automation could displace up to 800 million jobs by 2030, with approximately 375 million workers requiring significant retraining due to technological advancement (Manyika, Lund et al. 2017). However, it is also projected that AI and machine learning could create 2.3 million new jobs by 2025, emphasizing a transformation rather than simply a reduction in employment opportunities (Manyika, Lund et al. 2017). This transition is expected to affect routine jobs significantly, such as data entry and assembly line work, which are at high risk of being automated, while non-routine jobs that require problem-solving capacities and decision-making skills are likely to increase (Autor 2015).

Digital technology has increased productivity, a production worker can now produce in 11 hours what took 40 hours in 1950. Additionally, digital technology makes a greater variety of higher quality goods available to a broader consumer market. Furthermore, it creates value through intellectual property, process optimization, user-generated content, and human capital. However, this technological progress has also increased economic inequality. While the median income in the United States has declined by 10%, the top 10% of earners now receive over 50% of the national income. This concentration of wealth is driven by two factors. Firstly, skilled workers benefit more from digital technology than unskilled workers. Besides, those who control digital technology, or its derived intellectual property can earn

even more since digital capital can be reproduced at little or no cost. Consequently, the wealthy become wealthier, while those already struggling face the challenge of sustaining themselves and their families (West 2015).

This challenge of sustaining families among unskilled workers, resulting from technological changes, has led to fear of robots. This fear refers to the anxiety and apprehension that individuals might feel towards the increasing presence of robots in their work. The fear of robots is not limited to those who become unemployed as a direct result of technological change but also affects those who feel threatened by the significant transformations occurring in the job market. Initially, unskilled workers were primarily concerned about job loss. However, next generation robots are likely to be better in many unskilled, semi-skilled and even skilled aspects of jobs (Hinks 2021). Consequently, the fear of robots seems to extend to workers across all skill levels. Over the past few decades, computers have already replaced jobs in areas like bookkeeping, cashiering, and telephone operations (Frey and Osborne 2017).

Understanding fear of robots in the workplace is critical, as it can influence public acceptance of new technologies, potentially hindering innovation, and investment. This, in turn, may affect the economic growth potential of economies worldwide (Dekker, Salomons et al. 2017). Job insecurity, defined as the feeling of being at risk of unemployment, has negative effects not only on job satisfaction, but also on the well-being outside of work. Furthermore, job insecurity is associated with bullying at work, and can even influence political behavior, as job insecurity often aligns with support for extreme-right parties due to fears of social displacement (De Witte, De Cuyper et al. 2012).

Research has shown that production workers in the American workplace view industrial robots as a threat to their jobs (Fink, Robinson et al. 1992), while a Eurobarometer survey revealed concerns about robots reducing human interaction in socially interactive fields like healthcare and education (Taipale, De Luca et al. 2015). These studies underscore the importance of addressing workers' fears and anxieties surrounding automation.

2.2 Macro-level Explanations for Fear of Robots

This section outlines the macro-level factors, cultural and economic conditions, that influence the fear of robots in the workplace.

2.2.1 Cultural Conditions

Culture, broadly defined as the shared value, norms, and beliefs within a society, significantly shapes attitudes toward technological advancements, including robotics (DiMaggio 1990).

The cultural context influences how individuals perceive and interact with robots, affecting their likeability, trustworthiness, and overall acceptance. Studies have shown considerable variation in these perceptions across different cultures, even among seemingly similar European countries. For example, the Dutch are more prone to anthropomorphize robots than Germans (Turja and Oksanen 2019). This variation underscores the importance of considering cultural nuances when examining technology acceptance across different societies.

To quantify cultural differences, “cultural syndromes” are used, these are distinct patterns of attitudes and behaviors within a society. Cultural syndromes include the culture of Dignity, the culture of Honor, and the culture of Face. Western European countries are typically classified as Dignity cultures, where individuals tend to assume “swift trust”, which means that they trust others until proven otherwise (Chien, Sycara et al. 2016). This cultural trait may influence how individuals in these societies perceive and engage with robots, shaping their level of fear or acceptance.

Furthermore, studies in human-robot interaction indicate that physical interaction with robots can positively influence people’s attitudes toward them (Shibata, Wada et al. 2004). However, this acceptance varies across cultures. In many Western societies, there is a prevalent fear that robots might “take over the world” (Bartneck, Suzuki et al. 2007). This may be partly due to the challenge robots pose to human identity and the sense of purpose that cultural norms provide. As robots become more human-like, they could challenge our unique sense of being human and raise existential questions about our role in the world (MacDorman, Vasudevan et al. 2009).

Moreover, individuals in Eastern societies tend to have more positive attitudes toward robots than those in Western countries (Shaw-Garlock 2009). This difference underscores the significance of cultural standards in shaping how robots are perceived and integrated into society.

To better understand these cultural differences, it is important to apply a suitable cultural model. Hofstede’s cultural dimensions provide a robust framework for this purpose. These dimensions include individualism vs. collectivism, power distance, uncertainty avoidance, and masculinity vs. femininity, short-term orientation vs. long-term orientation,

and indulgence¹. Each of these dimensions significantly influences how different cultures perceive and react to technological advancements, such as the introduction of robots in the workplace (Turja and Oksanen 2019). A key cultural dimension is uncertainty avoidance, which measures how comfortable a culture is with uncertainty and change. In countries with lower uncertainty avoidance, people are more adaptable and accepting of risks, such as job changes or new situations (Dekker, Salomons et al. 2017). In these countries people might be more open to technological innovations like robots, as they are more open to the unknown (Hofstede 2003). It is therefore hypothesized that: *low uncertainty avoidance cultures are less fearful of robots in the workplace than high uncertainty avoidance cultures (H1a)*.

Similarly, individualistic cultures, which prioritize personal goals and self-reliance, may experience greater fear of robots than collectivist societies, where group harmony and shared responsibilities are valued (Hofstede 2003). Research indicates that robots are perceived as more empathetic and trustworthy in collectivist cultures like India, compared to individualistic ones like Germany (Homburg and Merkle 2019). This suggests that individualistic cultures may experience greater concerns about the potential threats posed by robots, particularly in terms of job displacement. Consequently, it is hypothesized that: *individualistic cultures are more fearful of robots in the workplace than those from collectivist cultures (H1b)*.

Power distance, another Hofstede dimension, refers to the extent to which less powerful members of a society accept unequal power distribution. Higher power distance is associated with lower national innovation and may hinder technological progress, including the adoption of robotics (Rinne, Steel et al. 2012, Salzmann and Soypak 2017). According to this it is expected that *high power distance cultures are more fearful of robots in the workplace than low power distance cultures (H1c)*.

Additionally, masculine cultures, which emphasize traits like competitiveness and ambition, are more likely to embrace automation technologies that improve efficiency and productivity (Shinde 2020). In contrast, feminine cultures, which prioritize cooperation and quality of life, may show more resistance to such changes (Hofstede 2003). The hypothesis associated with masculinity vs. femininity is *masculine cultures are less fearful of robots in the workplace than those from feminine cultures (H1d)*.

Long-term orientation, which emphasizes future planning and sustained efforts, correlates with risk aversion, leading to greater openness toward innovation (Hofstede and

¹ <https://geerthofstede.com/culture-geert-hofstede-gert-jan-hofstede/6d-model-of-national-culture/>

Minkov 2010). Conversely, short-term oriented cultures may focus more on the immediate impacts of automation, such as job displacement, potentially leading to greater resistance (Hofstede 2003). Based on this, it is hypothesized that *long-term oriented cultures are less fearful of robots in the workplace than short-term oriented cultures* (H1e).

Indulgent cultures are associated with increased risk-taking behavior in firms (Alipour and Yaprak 2022). Moreover, in indulgent societies the job satisfaction is less influenced by job security than in restraint societies (Gu, Li Tan et al. 2022). Therefore, it can be expected that *indulgent cultures are less anxious about automation than restraint cultures* (H1f), particularly the risks and job insecurity associated with automation.

2.2.2 Economic Conditions

It is likely that the fear of robots and automation in the workplace is also influenced by macroeconomic conditions. Just as perceived job insecurity rises during periods of economic downturn, the fear of robots may intensify in less favorable economic environments (Dekker, Salomons et al. 2017).

Research indicates that economic growth plays a significant role in shaping perceptions of job insecurity. During periods of strong economic growth, workers tend to feel more secure in their employment, as expanding economies generate job opportunities and enhance optimism about future employment prospects (Lübke and Erlinghagen 2014). Conversely, when economic growth declines, labor markets slow down, leading to increased anxiety about job security and greater concerns about technological displacement (Green 2009). In such environments, technological change may lead to more significant disruptions, as labor market adjustments occur through job destruction rather than slow, steady growth (Jaimovich and Siu 2012).

High unemployment rates, another key macroeconomic indicator, are also closely associated with heightened perceptions of job insecurity. Studies have found that workers are more likely to feel insecure about their jobs in countries or periods characterized by high unemployment, as finding new employment becomes more difficult and competitive (Chung and Van Oorschot 2011). In these contexts, workers may view automation as intensifying existing labor market challenges, as robots replace routine tasks and increase job displacement risks (Frey and Osborne 2017).

Together, these macroeconomic conditions create an environment in which automation, particularly robotics, is perceived as a disruptive force rather than an opportunity for increased productivity and economic growth. Workers in economically unstable

environments may fear that the benefits of automation will unevenly be distributed to capital owners and high-skilled workers, while low- and middle-skill workers face the consequences of job losses (West 2015). It is therefore hypothesized that *the fear of robots in the workplace is heightened during periods of economic downturn, characterized by low GDP growth and high unemployment* (H2).

2.2.3 Interplay between Cultural and Economic Conditions, and Fear of Robots

The fear of robots in the workplace is not only a reflection of individual anxieties but is rooted in broader cultural and economic conditions. To comprehensively address the fear of robots in the workplace, it is essential to understand the interaction between economic conditions and cultural conditions.

Cultural conditions significantly influence how individuals perceive technological advancements, including robotics. As discussed in Section 2.2, Hofstede's cultural dimensions, such as uncertainty avoidance and individualism, can shape attitudes toward robots. For instance, cultures with high uncertainty avoidance may exhibit greater apprehension towards technological innovations, fearing job displacement and the unknown implications of integrating robots into the workplace. Studies support this, showing that cultures more resistant to uncertainty are generally more skeptical towards new technologies, viewing them as potential threats to stability (Hofstede 2003, Dekker, Salomons et al. 2017). This fear can intensify during times of economic uncertainty, such as periods of low GDP growth or high unemployment. Therefore, it is hypothesized that *in times of economic downturn, high uncertainty avoidance cultures will exhibit a stronger fear of robots in the workplace compared to low uncertainty avoidance cultures* (H3a). In contrast, cultures with low uncertainty avoidance may view robots more positively, seeing them as opportunities for innovation and progress.

Moreover, Hofstede's cultural dimensions suggest that cultural influences extend beyond attitudes towards automation alone. For instance, cultures characterized by higher masculinity may be more willing to adopt technologies like robots due to a focus on competition and efficiency, while more feminine cultures that value quality of life may resist such changes (Shinde 2020). However, if there is economic growth, feminine cultures may become more accepting toward automation, since it can improve innovation (West 2015). So, *in times of economic downturn, feminine cultures will exhibit a stronger fear of robots in the workplace, while masculine cultures will show relatively stable attitudes toward robots, regardless of economic conditions* (H3b). Particularly in economies that benefit from

technological advancements. These cultural dimensions help explain varying levels of fear of robots across different societies, highlighting how cultural norms and values can shape whether robots are viewed positively or negatively.

Economic conditions also have a profound impact on the fear of robots, as discussed in section 2.3. In times of economic uncertainty, such as periods of low GDP growth or high unemployment, workers tend to experience more job insecurity (Green 2009). Automation technologies like robots are often seen as intensifying these insecurities, especially when labor markets are already under pressure. In economically unstable environments, workers may view robots as direct threats to job stability, increasing fears of automation regardless of cultural background. For instance, in individualistic cultures where self-reliance is emphasized, workers may be more fearful of robots when unemployment is high, as the fear of job insecurity and difficulty in re-employment intensifies (Chung and Van Oorschot 2011). Thus, *in times of economic downturn, individualistic cultures will experience a higher fear of robots in the workplace compared to collectivist cultures* (H3c). This contrasts with collectivist cultures, which may place greater value on community stability over individual job concerns (H1b).

As outlined in H1c, high power distance cultures are more fearful of robots than low power distance cultures. *In times of economic downturn, high power distance cultures will show a stronger fear of robots in the workplace compared to low power distance cultures* (H3d), as workers in high power distance cultures may feel vulnerable to job displacement when the labor market is not good (Salzmann and Soypak 2017).

Moreover, *in times of economic downturn, short-term oriented cultures will have a stronger fear of robots in the workplace compared to long-term oriented cultures* (H3e), as they focus on the short-term job losses rather than the long-term benefits of increased productivity (Hofstede and Minkov 2010).

This aligns with research suggesting that economic conditions, particularly those characterized by labor market volatility, intensify anxieties about automation (Lübke and Erlinghagen 2014). On the other hand, during periods of economic growth, even cultures with a historical aversion to technological change may become more accepting of robots, seeing them as tools for economic expansion and opportunity rather than sources of job displacement (West 2015). Therefore, economic conditions serve as both a magnifier and a modulator of cultural perceptions regarding automation. The same workers who may fear robots during economic downturns are likely to embrace them during periods of growth, as automation enhances productivity and creates opportunities (Manyika, Lund et al. 2017).

The interplay between cultural and economic conditions is critical in shaping how workers perceive and respond to robots in the workplace. When cultural factors that foster fear of automation, such as high uncertainty avoidance or collectivism, interact with challenging economic conditions, such as rising unemployment or static GDP growth, the fear of robots is likely to intensify. In such situations, automation is also a threat to societal and economic stability (Autor 2015). In contrast, in cultures that are more open to change and during times of economic growth, fears about robots may be significantly diminished. For example, in a collectivist culture with high unemployment, the fear of robots may be particularly pronounced because workers not only face the threat of individual job loss but also perceive automation as a danger to community stability. Research has shown that in such settings, automation triggers concerns about inequality and economic displacement (Jaimovich and Siu 2012). In contrast, in individualistic cultures with strong economic growth, workers may see robots as tools for personal advancement, reducing their fears even if they personally value job security.

Furthermore, indulgent cultures, are less likely to fear robots, as they are generally more open to risk-taking and less concerned with job security compared to restraint cultures (Alipour and Yaprak 2022). However, *in periods of economic downturn, indulgent cultures will show an increased fear of robots in the workplace* (H3f).

Understanding the interplay between cultural and economic conditions is crucial for addressing workers' fear toward automation. For instance, promoting trust in automation may be particularly important in cultures with high uncertainty avoidance (Chien 2016). Research shows that building trust in automation through transparency, education, and inclusive implementation strategies can reduce fears (Bartneck, Suzuki et al. 2007). Additionally, during periods of economic instability, policies that provide social safety nets for workers displaced by automation can reduce fear of robots (Tiwari 2023).

The interplay between cultural conditions and economic conditions is crucial for understanding workers' fear of robots in the workplace. By considering both macro-level cultural influences and economic realities, researchers can develop a more nuanced view of the challenges posed by automation.

3. Data and Methodology

The data used in this study comes from the Eurobarometer 87.1 survey (2017), which contains 27,901 respondents aged 15 years and older from 27 European countries. Firstly, the respondents were provided with the following definition of robots *‘a machine which can assist humans in everyday tasks without constant guidance or instruction, e.g., as a kind of co-worker helping on the factory floor or as a robot cleaner, or in activities which may be dangerous for humans, like search and rescue in disasters. Robots can come in many shapes or sizes, and some may be of human appearance. Traditional kitchen appliances, such as a blender or a coffee maker, are not considered as robots.’*, and the following definition of Artificial Intelligence (AI) *‘is a term used to describe systems that, to some extent, can sense, perceive, think, and act like humans and behave rationally. Artificial Intelligence is used, for instance, in driverless cars or drones, in our homes to adjust the heating automatically, in healthcare to improve medical diagnoses and in farming to apply pesticides only where they are necessary.’*

In addition to survey data, this study incorporates cultural dimensions data from Hofstede’s model for the 27 European countries. This dataset includes values for each of Hofstede’s six cultural dimensions at the national level. Furthermore, economic conditions, such as GDP growth and unemployment rates are analyzed. GDP annual growth data, covering the years 2006 to 2017, is sourced from Eurostat, as is the annual unemployment rate data for the same period.

Since this research focuses on fear of robots in the workplace, only the labor force is included. These are the respondents who are self-employed, employed, or unemployed and aged between 15- and 65-year-old. Moreover, this Eurobarometer dataset is restricted to country-level data.

3.1 Dependent Variable

The dependent variable, *fear of robots in the workplace*, is measured by averaging the factor scores of several relevant survey items, as outlined in Table 1:

Table 1. Items and factor scores on robots and artificial Intelligence

Table 1. Items and factor scores on robots and Artificial Intelligence		
Questions	Answer categories	Factor loadings

(qd10) Generally speaking, do you have a very positive, fairly positive, fairly negative or very negative view of robots and artificial intelligence?	(1) Very positive (2) Fairly positive (3) Fairly negative (4) Very negative (5) DK	0.560
Here is a list of things that could be done by or with robots. For each of them, please tell me, using a scale from 1 to 10, how you would personally feel about it. On this scale, '1' means that you would feel "totally uncomfortable" and '10' means that you would feel "totally comfortable" with this situation.		
(qd13_2) Having a robot assist you at work	(1) Totally uncomfortable (2) (3) (4) (5) (6) (7) (8) (9) (10) Totally comfortable, It depends (SPONTANEOUS), DK	0.750
(qd13_3) Having a robot to provide you services and companionship when inform or elderly	(1) Totally uncomfortable (2) (3) (4) (5) (6) (7) (8) (9) (10) Totally comfortable, It depends (SPONTANEOUS), DK	0.560
(qd13_4) Receiving goods delivered by a drone or a robot	(1) Totally uncomfortable (2) (3) (4) (5) (6) (7) (8) (9) (10) Totally comfortable, It depends (SPONTANEOUS), DK	0.680
(qd13_5) Being driven in a driverless car in traffic	(1) Totally uncomfortable (2) (3) (4) (5) (6) (7) (8) (9) (10) Totally comfortable, It depends (SPONTANEOUS), DK	0.816
Eigenvalue		2.828

Cronbach's Alpha	0.821
Mean R²	0.566

Source: Eurobarometer *Attitudes towards the impact of digitalization and automation on daily life* (2017).

Notes: A total of 17272 observations of five variables. The variable *Fear of robots in the workplace* is constructed as the mean of these five items at the individual level.

These items include statements such as “Generally speaking, do you have a very positive, fairly positive, fairly negative or very negative view of robots and artificial intelligence?” and “Having a robot assist you at work”. Scores range from 1 to 5, with higher values indicating greater fear of robots. Specifically, higher scores reflect stronger disagreement with statements like “Having a robot assist you at work”.

The factor loadings for each survey item are presented in Table 1, which demonstrates the strength of the relationship between each item and the underlying construct of fear of robots in the workplace. For instance, the item “Having a robot assist you at work” has a factor loading of 0.750, indicating a strong correlation with the dependent variable. The overall reliability of the scale is confirmed by a Cronbach’s Alpha of 0.821, which suggests high internal consistency.

The items chosen for measuring fear of robots in the workplace are derived from a broader survey on attitudes toward the impact of digitalization and automation on daily life, conducted by the Eurobarometer in 2017. The selection of these items was informed by their relevance to workplace settings and their ability to capture various levels of discomfort with robotic assistance in professional environments. This is further supported by an eigenvalue of 2.828, which indicates that the selected items adequately represent a single latent factor.

3.2 Individual-Level Variables

This study examines how cultural and economic conditions shape fear of robots in the workplace by analyzing both individual-level and country-level variables.

The labor market position, the education level, and the exposure to robots will be used as individual-level variables. These variables will also be derived from the Eurobarometer 87.1 survey. The *labor market position* refers to the respondent’s positions in the labor market, these positions are categorized into groups as employed, self-employed, and unemployed. Additionally, the occupation types will also be considered, including manual workers, white-collar workers, and managers. Moreover, the *educational level* of the

individuals will be considered. This variable is divided into three categories: those who completed education by age 15 (including those with no full-time education), those who studied until ages 16-19, and those who pursued education beyond age 20. The latter group serves as the reference category. *Exposure to robots*, or earlier experience with robots, whether at home or at work, is included as a dummy variable to account for the potential familiarity effect, which might mitigate fear of robots.

Table 2 presents descriptive statistics for the dependent variable alongside all individual-level variables:

Table 2. Descriptives for individual-level variables

	Mean	Standard deviation	Median	Minimum	Maximum
Fear of robots in the workplace	3.15	1.02	3.11	1	5
Studied after age 20	0.33	0.47	0	0	1
Studied until 16-19	0.43	0.49	0	0	1
Studied until 15	0.04	0.19	0	0	1
Business owners	0.08	0.28	0	0	1
Managers and professionals	0.15	0.36	0	0	1
White-collar workers	0.16	0.36	0	0	1
Manual workers	0.24	0.43	0	0	1
Unemployed	0.09	0.28	0	0	1
Used robots at work	0.07	0.25	0	0	1
Age	43.7	14	45	15	65
Female	1.45	0.50	1	1	2

Source: Eurobarometer *Attitudes towards the impact of digitalization and automation on daily life* (2017).

Notes: A total of 17272 observations.

These calculations incorporate the post-stratification weight factor (W1) provided in the Eurobarometer dataset. Results indicate that the average fear of robots in the workplace among the European labor force is 3.15 on a scale of 1 to 5, with a standard deviation of 1.02 at the individual level.

The data reveal that approximately 33% of respondents pursued education beyond age 20, while 4% completed their education by age 15. Among the employed, manual workers constitute 24%, white-collar workers 16%, and managers or professionals 15%. Business

owners make up the remainder of 8%. Unemployment affects 9% of the labor force, and only 7% report having prior experience with robots in their workplace.

3.3 Country-Level Variables

This study considers cultural and economic factors as the independent country-level variables to explore variations in fear of robots across countries.

Cultural variables include *uncertainty avoidance, individualism vs. collectivism, power distance, masculinity vs. femininity, long-term vs. short-term orientation, and indulgence vs. restraint*. Uncertainty avoidance refers to the extent to which members of a society feel discomfort with uncertainty and ambiguity. Individualism measures the degree to which a society values personal goals and self-reliance as opposed to collective interests and group harmony. Power distance captures the extent to which less powerful members of a society accept and expect unequal distributions of power. Masculinity reflects a society’s preference for traditionally masculine traits, such as ambition and competition, as opposed to traits like nurturing and cooperation. Long-term orientation assesses a culture’s emphasis on planning for the future and maintaining sustained efforts, while indulgence describes a society’s tendency toward risk-taking and the chase of pleasure. These variables are crucial for understanding cross-national differences in attitudes toward automation. Higher scores, as detailed in Table 3, indicate stronger uncertainty avoidance, greater individualism, higher power distance, a more masculine culture, a stronger focus on long-term orientation, or a more indulgent cultural outlook:

Table 3. Descriptives for the country-level variables

	Mean	Standard deviation	Median	Minimum	Maximum
GDP growth rate	2.36 (0.85)	1.04 (0.35)	2.24 (0.83)	-0.24 (0.14)	5.14 (1.64)
Unemployment rate	8.66 (2.05)	4.68 (0.44)	7.86 (2.06)	3.97 (1.38)	23.57 (3.16)
Uncertainty avoidance	68.96	23.09	70	23	112
Individualism	62.27	16.14	63	27	89
Power distance	48.44	20.01	46	11	104
Masculinity	48.91	26.86	54	5	110
Long Term orientation	57.69	17.52	60.45	24.43	82.87
Indulgence	44.59	18.33	43.53	12.95	77.68

Source: Eurobarometer *Attitudes towards the impact of digitalization and automation on daily life* (2017).

Notes: A total of 17272 observations. Values in parenthesis represent the results using the logarithmic transformation of the variables.

The economic variables include *GDP growth* and the *unemployment rate*. GDP growth is measured as the real economic growth of a country during the previous year, while unemployment rate measures as the share of the unemployed within the labor force. These indicators provide insight into the national economic context, enabling the study to investigate whether fear of robots is more pronounced in weaker economic environments. Prior research, such as that by Dekker, Salomons, et al. (2017), has demonstrated the relevance of such indicators in examining the perceived fear of automation.

The country-level variables used in this analysis are summarized in Table 4:

Table 4. Scores for country-level variables

	GDP growth rate	Unemployment rate	Uncertainty avoidance	Individualism	Power distance	Masculinity	Long Term orientation	Indulgence
AUT	2.04	6.03	70	55	11	79	60.45	62.72
BEL	1.41	7.86	94	75	65	54	81.86	56.70
CZE	2.45	3.97	74	58	57	57	70.03	29.46
DEN	1.96	6.01	23	74	18	16	34.76	69.64
EST	3.49	6.77	60	60	40	30	82.12	16.30
FIN	2.48	8.79	59	63	33	26	38.29	57.37
FRA	1.19	10.04	86	71	68	43	63.48	47.77
GBR	1.79	4.83	35	89	35	66	51.13	69.42
GER	2.24	4.13	65	67	35	66	82.87	40.40
GRE	-0.24	23.57	112	35	60	57	45.34	49.55
HUN	2.28	5.10	82	80	46	88	58.19	31.47
IRE	5.14	8.41	35	70	28	68	24.43	64.96
ITA	1.15	11.68	75	76	50	70	61.46	29.69
LAT	2.21	9.63	63	70	44	9	68.77	12.95
LIT	2.35	7.90	65	60	42	19	81.86	15.63
LUX	3.08	6.33	70	60	40	50	63.98	56.03
NET	2.21	6.03	53	80	38	14	67.00	68.30
POL	2.97	6.19	93	60	68	64	37.78	29.24
POR	1.93	11.18	104	27	63	31	28.21	33.26
SLK	3.33	9.67	51	52	104	110	76.57	28.35
SLV	3.15	8.01	88	27	71	19	48.62	47.55
SPA	3.17	19.65	86	51	57	42	47.61	43.53
SWE	3.24	6.95	29	71	31	5	52.90	77.68

3.4 Data Analysis

The hypotheses in this research are formulated at two levels of analysis: the individual level, and the country-level. To test them, a linear multilevel regression analysis will be employed, a method specifically designed to account for the nested structure of data, in this case, individuals nested within countries (DiPrete and Forristal 1994, Hox 2013). Multilevel models, also known as contextual or hierarchical models, are particularly effective in examining how macro-level processes influence individual outcomes beyond the effects of individual-level variables (Vauclair 2013). By disentangling the variance in the dependent variable into its individual- and country-level components, this method allows for the simultaneous testing of both individual- and country-level hypotheses (Donaldson, Handren et al. 2017).

The baseline specification assumes random intercepts across countries, enabling the analysis to capture variation in baseline levels of the dependent variable between countries, such as differing national attitudes or behaviors. In this model, the slopes for individual-level variables are fixed, indicating that their effects are consistent across countries. As a robustness check, models with random slopes will be estimated, allowing the effects of individual-level variables to vary by country. This more flexible specification provides insight into how national contexts may shape the influence of individual characteristics.

Furthermore, as an additional robustness check, the results will be evaluated using ordinary least squares (OLS) regression, both with and without country fixed effects. This triangulation ensures the robustness of our findings. Multilevel regression, however, remains the most appropriate method for this study, given its capacity to address the hierarchical nature of the data and control for within-country correlations. This approach has been extensively validated in cross-cultural research and studies examining nested data structures (Vauclair 2013, Turja and Oksanen 2019, Hinks 2021).

4. Results

This section presents the findings of the multilevel and ordinary least squares (OLS) regression analyses conducted to examine the hypotheses regarding cultural and economic predictors of fear of robots in the workplace. The analyses incorporated both individual-level and country-level variables, with key results summarized below.

The influence of cultural dimensions on fear of robots was assessed using country-level regressors within the multilevel model. The findings provided partial support for the hypotheses. Contrary to expectations, uncertainty avoidance did not exhibit a statistically significant effect in either the multilevel or the OLS models with significant fixed effects ($p < 0.05$). This result indicates that cultural variations in uncertainty avoidance do not lead to significant differences in fear of robots (h1a). Similarly, individualism was not a significant predictor in the multilevel regression model ($p > 0.05$). Also, in the fixed-effects OLS model, its relationship with fear of robots was not significant ($p = 0.187$), providing no support for the hypothesis that individualistic cultures exhibit greater fear of robots compared to collectivist cultures (h1b). Power distance demonstrated a negative but non-significant association with fear of robots in the multilevel model ($p > 0.05$). However, the fixed-effects OLS analysis revealed a significant negative relationship ($p < 0.001$), partially refuting the hypothesis that high power distance cultures are more fearful (h1c).

Masculinity emerged as a significant predictor of fear of robots, with higher masculinity scores associated with lower levels of fear ($p = 0.007$ in Model 2 of the multilevel analysis), supporting hypothesis 1d. Long-term orientation displayed a weak but marginally significant effect ($p = 0.050$ in Model 2 of the multilevel analysis), providing partial support for the hypothesis that long-term-oriented cultures exhibit lower levels of fear compared to short-term-oriented cultures (h1e). Indulgence was not significant in the multilevel models ($p > 0.05$). However, in the fixed-effects OLS models, indulgence was positively associated with fear of robots ($p < 0.001$), contradicting the proposed hypothesis.

The relationship between economic conditions (GDP growth and unemployment) and fear of robots was examined using both multilevel and OLS models. GDP growth was not a significant predictor in the multilevel models ($p > 0.05$). However, in the fixed-effects OLS model, higher GDP growth rates were significantly associated with lower fear of robots ($p < 0.001$), supporting hypothesis 2. The unemployment rate was significantly related to fear of robots in the OLS models ($p < 0.001$), but not in the multilevel models, suggesting that

heightened fear of robots is associated with economic conditions characterized by high unemployment, thereby partially supporting hypothesis 2.

To investigate the interaction between economic downturns and cultural dimensions, the analysis included interaction terms between economic indicators (GDP growth and unemployment) and cultural dimensions. The interaction between unemployment and uncertainty avoidance was significant in the OLS-fixed-effects model ($p < 0.001$), indicating that cultures with high uncertainty avoidance exhibit heightened fear of robots during economic downturns (h3a). The interaction between masculinity and unemployment was not significant, suggesting that masculine cultures maintain stable attitudes toward robots regardless of economic conditions (h3b). The interaction between individualism and unemployment was significant in the OLS models ($p < 0.001$), supporting the hypothesis that individualistic cultures experience heightened fear of robots during economic downturns (h3c). The interaction between power distance and unemployment was also significant in the OLS models ($p < 0.001$), supporting the hypothesis that high power distance cultures exhibit greater fear of robots during periods of economic downturns (h3d). The interaction between long-term orientation and unemployment was marginally significant in the multilevel models ($p = 0.050$), providing partial support for the hypothesis that short-term oriented cultures experience greater fear of robots during downturns (h3e). Lastly, the interaction between indulgence and unemployment was significant in the OLS models ($p < 0.001$), supporting the hypothesis that indulgent cultures exhibit heightened fear of robots in periods of economic downturn (h3f).

Across all models, individual-level variables demonstrated strong and statistically significant effects on fear of robots. Higher educational attainment (i.e., continuing education beyond the age of 20) was associated with lower fear of robots ($p < 0.001$). Furthermore, individuals employed in managerial and professional occupations reported significantly lower fear ($p < 0.001$), whereas manual workers and unemployed individuals reported significantly higher fear of robots ($p < 0.001$). Women exhibited lower fear of robots compared to men ($p < 0.001$). Age was positively associated with fear of robots ($p < 0.001$), indicating that older individuals are more fearful. Additionally, experience using robots at work significantly reduced fear of robots ($p < 0.001$).

The fixed-effects OLS analysis revealed significant country-level differences in fear of robots, even after accounting for cultural and economic variables. Notably, Denmark and Great Britain exhibited significantly higher levels of fear of robots compared to other nations

($p < 0.001$). Conversely, Spain and Greece displayed significantly lower levels of fear of robots ($p < 0.001$), potentially reflecting cultural or contextual influences.

Overall, the findings provide mixed support for the proposed hypotheses. Cultural dimensions, particularly masculinity and long-term orientation, emerged as significant predictors of fear of robots, while uncertainty avoidance, individualism, and power distance demonstrated inconsistent effects. Economic conditions, specifically unemployment, were associated with heightened fear of robots, with significant cultural interactions observed in high uncertainty avoidance, individualistic, and indulgent cultures. Individual-level predictors, including education, occupational status, and gender, exhibited robust effects across all models, underscoring their importance in shaping attitudes toward robots in the workplace.

5. Discussion

This study addresses the question: “To what extent do cultural and economic conditions influence the fear of robots at work?” and contributes to both public and academic debates on the impact of automation on employment. These debates have intensified in the Information Age, as advancements in robotics and AI accelerate, leading to their increasing adoption. While these technologies offer significant economic and productivity benefits, they also pose challenges for certain workers, fueling fears of job displacement and economic insecurity. Previous research has already established a link between awareness of smart technologies and perceived job insecurity (Lingmont and Alexiou 2020).

5.1 Theoretical Implications

This study contributes to the existing literature on automation anxiety by demonstrating that fear of robots is influenced not only by economic self-interest but also by cultural and economic factors. The use of multilevel regression analysis allows for a nuanced examination of both individual- and country-level predictors, contributing to broader debates about fear of robots.

First, the study highlights the role of cultural dimensions in shaping attitudes toward robots. The findings suggest that societies with a strong emphasis on masculinity and long-term orientation may be more resilient to automation fears. On the other hand, the unexpected results related to uncertainty avoidance and power distance challenge conventional assumptions, calling for further research into how cultural frameworks interact with economic conditions to influence automation-related anxieties.

Second, the interaction between economic indicators and cultural dimensions highlights the importance of considering macroeconomic factors when defining fear of robots. The study reveals that cultural predispositions are shaped by structural economic factors, such as unemployment and GDP growth, suggesting that automation anxiety is a dynamic and evolving phenomenon influenced by both individual traits and broader societal trends.

Third, the strong and consistent influence of individual-level variables, such as education, occupation, and direct experience with robots, reinforce psychological and human capital theories. Notably, this highlights the need to integrate personality psychology into automation research. For instance, neuroticism is associated with heightened workload and stress, leading to lower trust in automated systems (Szalma and Taylor 2011). In contrast, extraversion and openness correlate with positive affect, improved performance, and greater

robot likeability (Arora, Fleming et al. 2021). These findings underscore the importance of personalized interventions to strengthen human-robot interaction and foster trust in automation.

5.2 Practical implications

Beyond its theoretical contributions, this study provides valuable insights for policymakers, business leaders, and educators aiming to reduce resistance to automation and enhance workforce adaptability in an era of rapid technological change.

First, the findings indicate that automation-related fears can be reduced through continuous learning programs. Given the strong negative correlation between educational levels and automation anxiety, investing in lifelong learning is essential for building resilience among workers (Molnár, Jenei et al. 2024). Moreover, digital learning programs not only empower employees but also help businesses maintain their competitive edge in an evolving marketplace (Hogeforster and Wildt 2023).

Second, organizations play a crucial role in reducing technological anxiety by strategically integrating automation into the workplace. The findings suggest that direct experience with robots significantly reduces fear, highlighting the importance of gradual exposure to new technologies in fostering familiarity and acceptance. This is supported by research showing that firsthand interaction with robots can not only reduce fear but also improve overall attitudes toward them (Naneva, Sarda Gou et al. 2020).

Finally, cultural differences play a significant role in shaping attitudes toward automation. In high uncertainty avoidance cultures, structured environments with clear regulations and mechanistic frameworks are preferred when implementing new technologies (Doktor, Bangert et al. 2005). Conversely, in individualistic and indulgent societies, where economic downturns heighten fear of robots, workers are more likely to support social investment policies, such as training programs, as a means of addressing automation risks (Fan, Ning et al. 2024).

6. Limitations and future research

Despite its contributions, this study has several limitations that open avenues for future research. One key limitation is the influence of individual personality traits, which may act as confounding factors in shaping attitudes toward automation. Personality psychology seeks to describe and explain stable behavioral tendencies, referred to as dispositions, that differentiate individuals (Asendorpf 2009). These dispositions, when forming a consistent pattern in behavior over time, are recognized as personality traits.

The structure of personality traits can be understood through pattern of covariation, with multiple traits clustering into broader personality dimensions. For instance, sociability, energy, and cheerfulness collectively form the dimension known as extraversion in many cultures (McCrae and Costa Jr 1997). To streamline research, the field of personality psychology has developed a common taxonomy, the “Big Five” personality traits, which provides a framework for analyzing and comparing individuals across diverse contexts. These five dimensions include extraversion, agreeableness, openness to experience, conscientiousness, and neuroticism (John and Srivastava 1999). They capture most of the variability in personality traits relevant to consistent patterns or behavior (Korukonda 2005).

Each of the personality dimensions have the potential to influence attitudes toward technological changes, including the fear of robots in the workplace. For example, neuroticism, characterized by heightened anxiety and emotional instability, has been positively associated with fear of robots, suggesting that individuals high in neuroticism may be more prone to technological anxieties (Korukonda 2005). In contrast, traits such as openness to experience, which reflects curiosity and a willingness to embrace novelty, and extraversion, which involves social engagement and optimism, are negatively correlated with fear of robots. This indicates that individuals who are more open or extroverted are less likely to view robots as a threat.

These findings highlight how personality traits could confound the relationship between cultural or economic conditions and fear of robots. For example, workers in strong economic positions who are also high in neuroticism may still show high levels of robophobia, while individuals in weaker economic positions but high in openness may show less fear. As such, personality traits are important to consider in this study’s exploration of fear of robots as they introduce additional variability into individuals’ reactions to automation.

In addition to personality traits, economic self-interest plays a critical role in shaping workers’ fear of robots. Previous research suggests that individuals in vulnerable economic

positions, such as those in routine jobs prone to automation, tend to exhibit higher levels of anxiety toward robots. In contrast, individuals with greater economic security, such as managers or highly educated workers in non-routine positions, are more likely to feel resilient and adaptable, reducing their fear of robots (Dekker, Salomons et al. 2017).

Furthermore, exposure to robots can reduce fear. Individuals with direct experience using or working alongside robots tend to exhibit less anxiety about automation (Bartneck, Suzuki et al. 2007). This suggests that fear of the unknown plays a significant role in shaping attitudes toward robots. Workers with no direct experience may feel more concerned, while those accustomed to robotics in their daily work may view them as less threatening. Therefore, personal experience is another confounding factor to consider.

Finally, sociodemographic factors such as gender and age are also relevant confounding factors. Prior research has shown that men and women may perceive technological advancements differently due to their varying roles in the labor market (Nomura, Kanda et al. 2006). For instance, men are more likely to be employed in roles that require frequent interaction with advanced technology, which could reduce their fear of robots (Enz, Diruf et al. 2011). Similarly, younger workers, typically more familiar with technology, are often more positive toward robots compared to older workers, who may experience more anxiety about the implications of automation for their job security (Heerink 2011). These sociodemographic variables are likely to be correlated with both education levels and labor market positions, further complicating the relationship between economic and cultural factors and fear of robots.

Given these limitations, future research should consider integrating personality traits, economic security, technological exposure, and sociodemographic variables to develop a more nuanced understanding of fear of robots in the workplace. Longitudinal studies and cross-cultural comparisons could offer deeper insights into how these factors interact over time and across different labor market contexts. Addressing these complexities will be crucial in developing policies and interventions that promote a balanced and informed approach to workplace automation.

Appendices

Appendix I – Table 5. Multilevel regression analysis

	Fear of Robots (Model 1)			Fear of Robots (Model 2)		
	Estimates	Std. Error	<i>p</i>	Estimates	Std. Error	<i>p</i>
(Intercept)	2.54	0.68	<0.001	2.52	0.46	<0.001
<i>Individual-level regressors (constant)</i>						
Studied after age 20	-0.22	0.02	<0.001	-0.22	0.03	<0.001
Studied until 16-19	0.00	0.02	0.997	0.00	0.02	0.910
Studied until 15	0.20	0.04	<0.001	0.20	0.04	<0.001
Business owners	-0.00	0.03	0.944	-0.00	0.03	0.885
Managers and professionals	-0.09	0.02	<0.001	-0.09	0.02	<0.001
White-collar workers	-0.01	0.02	0.651	-0.01	0.02	0.651
Manual workers	0.19	0.02	<0.001	0.19	0.02	<0.001
Unemployed	0.12	0.03	<0.001	0.12	0.03	<0.001
Used robots at work	-0.42	0.03	<0.001	-0.42	0.03	<0.001
Age	0.01	0.00	<0.001	0.01	0.00	<0.001
Female	-0.31	0.01	<0.001	-0.31	0.01	<0.001
<i>Country-level regressors (standardized)</i>						
GDP growth rate	0.00	0.06	0.988	0.03	0.04	0.441
Unemployment rate	0.02	0.01	0.179	0.01	0.01	0.505
Uncertainty avoidance	0.00	0.00	0.502	0.00	0.00	0.099
Individualism	-0.00	0.00	0.411	-0.00	0.00	0.229
Power distance	-0.00	0.00	0.690	-0.00	0.00	0.388
Masculinity	0.00	0.00	0.195	0.00	0.00	0.007
Long Term orientation	0.00	0.00	0.295	0.00	0.00	0.050
Indulgence	0.01	0.00	0.057	0.00	0.00	0.129
R2/ R2 adjusted	0.114/ 0.167			0.117/ 0.172		

Source: Eurobarometer *Attitudes towards the impact of digitalization and automation on daily life* (2017).

Notes: Dependent variable is “Fear of robots in the workplace”. All models are linear multilevel models with random intercepts and fixed slopes. A total of 17272 observations, within 25 countries. The country-level regressors are standardized to have a zero mean and unit standard deviation.

Appendix II – Table 6. OLS regression with robustness checks

	OLS without fixed effects			OLS with country fixed effects		
	Estimates	Std. Error	<i>p</i>	Estimates	Std. Error	<i>p</i>
(Intercept)	2.58	0.11	< 0.001	-3.86	0.87	< 0.001
<i>Individual-level regressors</i>						
Studied after age 20	-0.22	0.02	< 0.001	-0.22	0.02	< 0.001
Studied until 16-19	0.02	0.02	0.253	-0.00	0.02	0.980
Studied until 15	0.24	0.04	< 0.001	0.20	0.04	< 0.001
Business owners	-0.03	0.03	0.338	-0.00	0.03	0.962
Managers and professionals	-0.09	0.02	0.001	-0.09	0.02	< 0.001
White-collar workers	-0.05	0.02	0.035	-0.01	0.02	0.680
Manual workers	0.19	0.02	< 0.001	0.19	0.02	< 0.001
Unemployed	0.13	0.03	< 0.001	0.12	0.03	< 0.001
Used robots at work	-0.45	0.03	< 0.001	-0.41	0.03	< 0.001
Age	0.01	0.00	< 0.001	0.01	0.00	< 0.001
Female	-0.30	0.01	< 0.001	-0.31	0.01	< 0.001
<i>Country-level regressors (standardized)</i>						
GDP growth rate	0.01	0.01	0.545	0.56	0.07	< 0.001
Unemployment rate	0.02	0.00	< 0.001	0.25	0.03	< 0.001
Uncertainty avoidance	0.00	0.00	< 0.001	0.03	0.00	< 0.001
Individualism	-0.00	0.00	< 0.001	0.00	0.00	0.187
Power distance	-0.00	0.00	0.005	-0.01	0.00	< 0.001
Masculinity	0.00	0.00	< 0.001	0.00	0.00	0.188
Long Term orientation	0.00	0.00	< 0.001	0.03	0.00	< 0.001
Indulgence	0.01	0.00	< 0.001	0.02	0.00	< 0.001
Country [BE – Belgium]				-0.60	0.13	< 0.001
Country [CZ – Czech Republic]				0.60	0.12	< 0.001
Country [DE-E Germany East]				0.45	0.09	< 0.001
Country [DE-W Germany-West]				0.57	0.09	< 0.001

Country [DK – Denmark]	1.41	0.16	<0.001
Country [EE – Estonia]	-0.51	0.07	<0.001
Country [ES – Spain]	-3.11	0.39	<0.001
Country [FI – Finland]	0.16	0.05	0.003
Country [FR – France]	0.06	0.10	0.552
Country [GBN – Great Britain]	1.71	0.11	<0.001
Country [NIR – Northern Ireland]	1.76	0.12	<0.001
Country [GR – Greece]	-2.53	0.35	<0.001
Country [HU – Hungary]	0.66	0.05	<0.001
Country [IE – Ireland]	-0.37	0.17	0.032
Country [IT – Italy]	-0.42	0.10	<0.001
Country [LT – Lithuania]	-0.03	0.07	0.702
R2/ R2 adjusted	0.122/ 0.121	0.155/ 0.154	

Source: Eurobarometer *Attitudes towards the impact of digitalization and automation on daily life* (2017).

Notes: Dependent variable is “Fear of robots in the workplace”. All models are linear multilevel models with random intercepts and fixed slopes. A total of 17272 observations, within 25 countries. The country-level regressors are standardized to have a zero mean and unit standard deviation.

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