Research Policy 53 (2024) 104987

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Robots, meaning, and self-determination

Milena Nikolova [a,b,c,d,*], Femke Cnossen [a,d], Boris Nikolaev [e,d]

[a] University of Groningen, Faculty of Economics and Business, Global Economics and Management, Groningen, the Netherlands
[b] Institute of Labor Economics (IZA), Bonn, Germany
[c] The Brookings Institution, Washington, DC, USA
[d] Global Labor Organization (GLO), Essen, Germany
[e] Colorado State University, College of Business, Fort Collins, CO 80523, USA

ARTICLE INFO

JEL codes:
J01
J30
J32
J81
I30
I31
M50

Keywords:
Work meaningfulness
Self-determination theory
Robotization
Automation

ABSTRACT

This paper is the first to examine the impact of robotization on work meaningfulness, autonomy, competence, and relatedness, which are essential to motivation and well-being at work. Using surveys of workers and robotization data for 14 industries in 20 European countries spanning 2005–2021, we find a consistent negative impact of robotization on perceived work meaningfulness and autonomy. Using instrumental variables, we find that doubling robotization leads to a 0.9 % decrease in work meaningfulness and a 1 % decline in autonomy. To put this in perspective, if the robotization levels of the top 5 industry were to match those of the leading industry in terms of robot adoption in 2020 (equivalent to a 7.5-fold increase), it would result in a decline of 6.8 % in work meaningfulness and 7.5 % in autonomy. The link between robotization, competence, and relatedness is also negative but less robust. We also examine how tasks, skills, and socio-demographic characteristics moderate the main relationships. We find that workers with routine tasks experience an even greater negative effect of robotization in terms of declines in their autonomy, competence, and relatedness. However, we also discover that utilizing computers as tools for independent work can help workers maintain a sense of autonomy, competence, and relatedness in industries and job roles that adopt robots. Our results highlight that by deteriorating work meaningfulness and self-determination, robotization can impact work life above and beyond its consequences for employment and wages.

1. Introduction

Robots are matching or outperforming humans in a growing range of tasks, including welding, packing, painting, filling prescriptions, and assembling intricate automotive parts. With the integration of artificial intelligence (AI), smart machines are now pioneering new frontiers, from performing complex surgeries on Earth, to exploring the harsh, uncharted surface of Mars. This ongoing wave of automation is arguably one of the most powerful forces that has already reshaped and will continue altering work in the future.

This rapid technological advancement has understandably sparked widespread fears about the future of work (e.g., Dekker et al., 2017; Hinks, 2021), reigniting age-old anxieties concerning the impact of technology on employment (e.g., Mokyr et al., 2015; Spencer, 2023). Recent projections on which jobs may be susceptible to automation (i.e., have automation potential) (Bonin et al., 2015; Bowles, 2014; Frey and Osborne, 2017; Pajarinen and Rouvinen, 2014) have recently rekindled debates and public fears.[1] While subsequent studies show much lower automation potentials across countries (Arntz et al., 2017, 2016; Nedelkoska and Quintini, 2018), the underlying fear of unemployment is understandable given the large earnings (e.g., Couch and Placzek, 2010; Huckfeldt, 2022) and psychological costs of unemployment (e.g., Nikolova and Ayhan, 2019; Kassenboehmer and Haisken-DeNew, 2009), and the fact that automation's consequences are negative for low-and middle-skilled workers and those performing routine tasks (e.g., Acemoglu et al., 2023; Acemoglu and Restrepo, 2020). Unsurprisingly, academic research has primarily focused on the repercussions of technology on employment and wages.

However, recent developments have fostered a broader understanding of automation's impacts. Models of routine-biased

* Corresponding author at: University of Groningen, Faculty of Economics and Business, Global Economics and Management, Groningen, the Netherlands.
E-mail addresses: m.v.nikolova@rug.nl (M. Nikolova), f.d.cnossen@rug.nl (F. Cnossen).

[1] In 2021, only 29 % of European respondents believed that artificial intelligence and automation would create more jobs than they would eliminate (European Commission, 2021).

https://doi.org/10.1016/j.respol.2024.104987
Received 27 June 2022; Received in revised form 30 January 2024; Accepted 27 February 2024
Available online 12 March 2024

technological change suggest that the job losses from automation can be counterbalanced by productivity and reinstatement effects (Acemoglu and Restrepo, 2019; Arntz et al., 2019), potentially leading to a net economic gain at the societal level (e.g., Gregory et al., 2021). Moreover, when firms adopt new technologies, workers adapt their tasks (Dauth et al., 2021; Spitz-Oener, 2006), which is why whole professions typically do not disappear. Nevertheless, the replacement of some tasks can lead to a reduction in task variety and autonomy. Therefore, how robotization affects job quality and how various tasks impact worker well-being are critical questions that the current literature on the employment and earnings effects of automation has yet to explore.

This paper advances previous research by providing a more holistic picture of the impact of robotization on workers' lives. Beyond income and job security, workers also value other aspects of their jobs that contribute to their well-being and motivation. For example, workers care about whether their work is meaningful or fulfilling (Hu and Hirsh, 2017; Kesternich et al., 2021), whether they have autonomy or discretion over their tasks, feel competent in executing their activities, and have positive relationships with their co-workers or clients (Deci and Ryan, 1985; Hackman and Oldham, 1976). These factors, intrinsic to human motivation and basic psychological needs, have profound effects on performance, productivity, and learning outcomes, and are key to optimal human functioning (Ryan and Deci, 2017; Ryan and Deci, 2001). Therefore, it is important to examine how automation affects non-monetary aspects of work quality and how workers can cope with the challenges and opportunities that automation brings.

This paper contributes to the literature by examining the impact of one type of automation— industrial robots— on two key aspects of work quality: work meaningfulness and self-determination. Work meaningfulness refers to the extent to which workers perceive their work as valuable, significant, or purposeful (Nikolova and Cnossen, 2020; Rosso et al., 2010). Self-determination denotes the extent to which workers experience autonomy, competence, and relatedness (Ryan and Deci, 2017). These aspects are derived from the seminal model in psychology: self-determination theory (Ryan and Deci, 2017). According to Nikolova and Cnossen (2020), autonomy, competence, and relatedness are key pre-conditions to achieving work meaningfulness. Furthermore, work meaningfulness is instrumental in workers' efforts and has been linked to key organizational outcomes such as absenteeism, retirement intentions, and the willingness to take on skills training (Nikolova and Cnossen, 2020; Rosso et al., 2010).

Industrial robots are capable of interacting with their environment by handling or moving objects and primarily perform routine manual tasks, such as reaching and handling.[2] Adopting industrial robots in the workplace can affect work meaningfulness and self-determination through several channels. For example, it can lead to diminishing human interactions and worsening relationships at work. Automation can also reduce workers' creativity and learning potential and diminish skill utilization and competence development, especially for those performing routine or manual tasks. In addition, industrial robots could reduce workers' autonomy if robots and algorithms determine their tasks and work sequence (Gombolay et al., 2015).

Robotization need not be harmful to work meaningfulness and self-determination. For instance, automation can also reduce "the drudgery of work" by eliminating repetitive tasks and freeing up time for creative pursuits (Spencer, 2018), which can improve job quality and the ability of workers to satisfy their innate psychological needs from work (Deci & Ryan, 2000). For example, by replacing dangerous or dull tasks, robots can improve working conditions, which can increase work meaningfulness and self-determination. Indeed, robots are already taking over tasks related to high-risk military operations, space explorations, bomb detection, and detonation, as well as "dirty" jobs, such as sewer cleanup, milking cows, or conducting autopsies (Marr, 2017). The adoption of such technologies can free humans to have more time and space to focus on creative tasks, especially those that require human judgment or interaction. Thus, the extent to which robots affect workers' perceptions of work meaningfulness and self-determination remains an empirical question.

We use worker-level survey data for 2010, 2015, and 2021 from 20 European countries and 14 industries to explore how automation technologies impact workers' meaningfulness and self-determination. We combine these data with industry-level information on changes in robots per 10,000 workers (i.e., robotization) and analyze the data using Ordinary Least Squares (OLS) and Instrumental Variable (IV) techniques.

Our key finding is that robots harm work meaningfulness and autonomy. Specifically, based on the IV coefficient estimates, doubling robotization would entail a 0.9 % decline in work meaningfulness and a 1 % drop in autonomy. Across all industries in our sample, the average increase in robotization between 2005 and 2020 was 389 % (almost a four-fold increase). For some industries, the increase was even more dramatic. In mining and quarrying, for instance, there was a staggering 26-fold increase in robotization over the same period, implying a substantial loss in meaningfulness and autonomy. To further put our estimates in perspective, consider the food and beverages industry, a top 5 industry in robot adoption, and the automotive industry (the sector with the highest level of robot adoption). Should robot adoption in the food and beverages industry increase to match that of the automotive industry (representing a 7.5-fold increase in robotization), we estimate a 6.8 % decrease in work meaningfulness and a 7.5 % decrease in autonomy. Based on EUKLEMS data, in 2020, nearly 4.5 million individuals worked in the food and beverages industry and about 3.3 million in the automotive industry across the countries in our study. Therefore, the impact sizes we document may seem small in isolation, but the cumulative and long-term effect could be substantial given the large number of employees affected in such sizable industries and long-term trends in robotization.

Furthermore, we find that the negative consequences of robotization for work meaningfulness are mostly independent of workers' tasks, skills, and socio-demographic characteristics. We do, however, find important heterogeneity related to autonomy. Specifically, working with computers — i.e., being in control of the machine — completely offsets the negative consequences of automation for autonomy. Having some tertiary education and being high-skilled cushions some of the negative effects of robotization on workers' autonomy as well. At the same time, the detrimental effects of robotization are more pronounced for workers performing repetitive tasks. Our research highlights that the groups disproportionately affected by robotization broadly overlap with those identified in prior studies focusing on wages (e.g., Acemoglu et al., 2023; Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018). With respect to competence and relatedness, the results also appear to be more strongly negative for those engaged in repetitive tasks and fully offset for those working with computers.

Overall, our study contributes to the scarce literature on the well-being implications of automation technology by examining how robotization affects workers' perceptions of meaningfulness and the fulfillment of their basic psychological needs of autonomy, competence, and relatedness. More generally, the unique contribution of our study lies in documenting how robotization can benefit or disadvantage various groups of workers in terms of their perceived work quality above and beyond its impact on wages and employment contracts. Importantly, we also highlight which tasks and arrangements could help workers adapt and leverage automation technology more effectively. While future patterns of robotization remain uncertain, our results provide a useful framework and baseline for understanding their effects on job quality and well-being outcomes.

[2] In this paper, we focus on industrial robots, rather than service robots used, for example, in surgery. The reason for the restriction is that industrial robots have seen by far the most adoption, whereas the adoption of service sector robots is still in its infancy during our analysis time period.

2. Literature review

The extant literature has mainly focused on the impact of robotization on employment and wages without reaching a consensus about the overall effects. The main conclusions depend on multiple factors, including the level of analysis – firm, industry, or worker – and the country context (the US, cross-country, or Europe). Robot-adopting firms, which are typically more productive than their counterparts, tend to expand their employment (Acemoglu et al., 2023; Acemoglu et al., 2020; Bessen et al., 2020; Dixon et al., 2021; Koch et al., 2021), and may even increase workers' wages (e.g., Bessen et al., 2020). At the same time, their non-robot-adopting competitors experience the opposite effects, reducing employment. These effects may result in an overall decline in employment at the economy level.

At the industry level, the evidence for some countries is negative, and for others not. Across 17 advanced economies, robotization has led to increases in wages overall but declines in the hours worked among the low-skilled (Graetz and Michaels, 2018). Furthermore, Acemoglu and Restrepo (2020) show that robot adoption between 1990 and 2007 led to large declines in employment and wages in US commuting zones. Similarly, Borjas and Freeman (2019) estimate that robotization entailed wage and employment declines between 2014 and 2016 in the US. In China, robot adoption also negatively affects employment and wages across cities for the 2000–2016 period (Giuntella et al., 2022). Adachi et al. (2022) found that robot adoption in Japanese industries and regions increased employment and wages in the 1978–2017 period. The French evidence on robots and employment is also positive with no consequences for wages (Aghion et al., 2020). Using data on 98 EU regions during the 2001–2016 period, Jestl (2023) finds relatively modest effects of robotization on total employment. There are negative consequences for local manufacturing industries, which are offset by employment in local services industries (Jestl, 2023). This evidence is in line with the German findings that industrial robots displace manufacturing workers, but this is offset by job creation in the services sector (Dauth et al., 2021).

The evidence on the wages and employment of individual workers is not only mixed but also scarce. The cross-country evidence for 20 European countries suggests that robots increased the wages of both male and female workers (Aksoy et al., 2021). When looking at individual workers in Germany, Dauth et al. (2021) find that robotization is associated with small employment increases and small wage declines, on average. In the Netherlands, robots increase the average hourly wages and decrease the hours worked, with no average consequences for employment (Acemoglu et al., 2023). Nevertheless, blue-collar, low-educated workers, and those performing routine tasks tend to see their wages decline (Acemoglu et al., 2023).

While the literature on robotization is rapidly expanding, economists have paid little attention to its impact on the job quality of individual workers (see a discussion in Berg et al., 2023). Investigating how automation influences job quality beyond wages and employment can significantly enhance our understanding of the broader consequences of robotization on workers' well-being. Factors beyond financial compensation, such as autonomy and a sense of meaning, play a crucial role in defining the comprehensive value of a job (e.g., Clark, 2015; Green, 2006; Nikolova and Cnossen, 2020) and are essential elements for evaluating the broader impact of technological change on the workforce.

The existing body of research on the effects of robotization on health and well-being outcomes, however, is still very limited (see Table 1).[3] Documented outcomes differ based on the period, context, and dependent variables. Some studies suggest that robotization seems to positively affect the health of low-skilled US workers by reducing physically demanding tasks, but does not affect high-skilled workers (Gunadi and Ryu, 2021). Other studies from the US find that while workplace injuries decline (Gihleb et al., 2022), there are decreases in mental health (Gihleb et al., 2022) and increases in substance-abuse-related deaths (Gihleb et al., 2022; O'Brien et al., 2022) and mortality from suicide, homicide, cancer, and cardiovascular causes in certain age groups (O'Brien et al., 2022). The evidence on the health consequences for Germany is more mixed, with Gihleb et al. (2022) finding no effects on mental health, and Abeliansky and Beulmann (2021) finding negative effects. Studies link automation to worsened job satisfaction in Norway, driven by low-skilled workers (Schwabe and Castellacci, 2020) and greater work intensity in Europe (Antón et al., 2023). Specifically, Antón et al. (2023) examined the effects of robot adoption on job quality and working conditions, focusing on elements, such as work intensity (e.g., the pace of work, time pressure, etc.), the physical environment, and skill discretion (Antón et al., 2023). Their findings suggest that an increase in the robot stock at the regional level is associated with higher work intensity but has no effect on any other job quality indicator related to the physical environment.

While the existing literature offers preliminary insights into the varying impact of robotization on workers' health and well-being, it also underscores the significant role of automation in shaping job quality. Adopting industrial robots can harm job satisfaction by inducing greater fear of future machine replacement. For example, studying a large sample of workers in Norway for the period 2016–2019, Schwabe and Castellacci (2020) find that introducing industrial robots in local labor markets increases workers' fear of machine replacement, which, in turn, significantly decreases their job satisfaction. Remarkably, 40 % of workers in their sample report fear that smart machines will substitute their working tasks in the future, a percentage that is similar to other European countries. The results reported by Schwabe and Castellacci (2020) are predominantly driven by low-skilled workers who, due to their routine-based tasks, are more likely to be exposed to automation.

A related body of work suggests that *automation risk*—typically associated with expectations of reduced wages and potential future unemployment—can also negatively impact workers' physical and mental health (e.g., Lordan and Stringer, 2022; Patel et al., 2018). Specifically, job-loss-related fear and anxiety can lead to job insecurity (Reichert and Tauchmann, 2017), subsequently culminating in poor physical and mental health outcomes (De Witte et al., 2016). Indeed, using data from the General Social Survey in the US, Patel et al. (2018) find that a 10 % increase in automation risk at the county level is associated with 2.38, 0.8, and 0.6 percentage points lower general, physical, and mental health, respectively. Similarly, Gorny and Woodard (2020) use data from the US and Europe to show that workers in occupations with higher *automation potential* through computer-controlled equipment are more likely to experience lower job satisfaction. However, they find that it is the monotonicity and low perceived meaning of such jobs that drive low job satisfaction rather than fears of future job replacement. Their results emphasize the crucial role job meaning plays in the relationship between robot adoption and subjective well-being outcomes such as job satisfaction.

Our study advances this emerging body of literature by examining the effect of robotization on work meaning and self-determination (i.e., competence, relatedness, and autonomy). This is important because prior research underscores that these dimensions do not merely enrich job experiences, but serve as key drivers of workers' motivation, effort, and performance (e.g., Nikolova and Cnossen, 2020) and are key aspects of the overall value of a job.

[3] See Castellacci and Tveito (2018) for an overview of the literature on well-being and ICT and Martin and Hauret (2022) for a summary of the studies on the effects of digitalization, including robotization and automation risk, on different measures of job quality.

Table 1
Related literature.

Reference	Outcomes	Automation measure	Level of analysis	Main data sources	Econometric technique(s)	Key findings
Health						
Abeliansky and Beulmann (2021)	Mental health	Robot stock per 1000 workers at the industry level	Individual-level	German Socio-Economic Panel, International Federation of Robotics (IFR), WIOD trade data, Baumgarten et al. (2013) task content data	Individual Fixed Effects; IV (instrument = robotization in other advanced countries)	Worse mental health; driven by job insecurity fears, especially for routine-task workers and males
Gunadi and Ryu (2021)	Share reporting i) poor health; ii) work disability; iii) quitting a job because of health	Robot stock per 1000 workers at the metropolitan statistical area (MSA) level	MSA-level in the US	Current Population Survey + IFR data on robots (2006–2017)	2SLS regressions (instrument = robot adoption in select European countries)	Reductions in share reporting poor health, work disability, and job quitting due to health among low-skilled workers; no effects for high-skilled workers;
Gihleb et al. (2022)	Workplace injuries, job intensity, disability, mental health, work and life satisfaction	Robot stock per US worker (for the US); Robot stock per German worker based on the initial occupation (German sample)	City-level (US), Individual-level (Germany)	Occupational Health and Safety Administration (OSHA) Data Initiative; Center for Disease Control and National Center for Health Statistics; American Community Survey (ACS); Behavioral Risk Factor Surveillance System (BRFSS); German Socio-Economic Panel (1994–2016); International Federation of Robotics (IFR)	IV (instrument = robot adoption in other countries, only for the US but not for analyses for Germany)	US: declines in workplace injuries; increase in drug- and alcohol-related deaths and worse mental health; Germany: less physical intensity; less disability; no effects on mental health and work/life satisfaction
Job satisfaction and job quality						
Schwabe and Castellacci (2020)	Job satisfaction	Fear of machine replacement, instrumented using the robot stock	Individual	Norway, 2007–2019, Working Life Barometer, International Federation of Robotics (IFR), Eurostat employment data	IV (instrument = lagged change in the robot stock per 1000 workers at the region-industry level)	Worse job satisfaction; driven by low-skilled workers (more exposed due to routine tasks)
Antón et al. (2023)	Job quality aspects (work intensity, physical environment, skills & discretion)	Change in the robot stock per worker at the regional (NUTS-2) level	Regional	European Working Conditions Surveys (1995–2005), International Federation of Robotics (IFR), European Union Labour Force Survey, European Community Household Panel, EUKLEMS	IV (instrument = change in the robot stocks in other advanced countries)	Worsens work intensity; No effects on any other job quality indicators

3. Conceptual framework

3.1. Meaningful work and self-determination

Work meaningfulness is a critical aspect of subjective job quality that matters for motivation and work effort (Cassar and Meier, 2018; Nikolova and Cnossen, 2020). People derive meaning from the intrinsic value of their work when they think they engage in useful, interesting, or fulfilling activities. In this sense, work meaningfulness is a psychological state that depends on the workers' perception of their jobs as valuable and worthwhile (Hackman and Oldham, 1976).

When people feel that their efforts are important for successfully executing a certain task, they tend to strongly identify with that goal. As a result, they are relatively more likely to experience meaning compared with a situation when they do not identify themselves with the objective. The inner drive to experience a sense of meaning at work is so strong that, on average, people are willing to accept a 38 % salary cut to engage in more meaningful work—$32,666 for a meaningful job vs. $52,498 for a meaningless job (Hu and Hirsh, 2017). Similarly, experimental studies from the US and Germany demonstrate that work meaningfulness lowers reservation wages (Ariely et al., 2008; Kesternich et al., 2021), yet only among those for whom work meaningfulness is very important in the German case (Kesternich et al., 2021).

Simultaneously, feelings of self-determination are based on three separate but complementary psychological needs: competence, autonomy, and relatedness (Deci and Ryan, 1985; Ryan and Deci, 2017). Workers feel competent when their skills match the complexity of the task. In such cases, when employees know that their skills are instrumental to the task at hand, they feel a greater sense of contribution. When a task is too easy, they feel like anyone could have done it, and when it is too hard or complex, they feel less self-efficacy and personal contribution. Therefore, feeling competent in the workplace is an important aspect of self-determination.

Second, people feel a sense of autonomy when they have "freedom, independence, and discretion" to make decisions regarding the planning and execution of their tasks (Hackman and Oldham, 1976). Promoting own initiatives and encouraging decision-making at the individual level, as opposed to traditional top-down directives, can foster an environment where employees feel an enhanced sense of control over their work.

Finally, according to self-determination theory, people have a deep psychological need for connectedness and belonging: they want to feel appreciated and supported by their co-workers and managers in their efforts at the company. Such high-quality relationships at work are also important for fostering work meaningfulness (Bailey et al., 2019), especially when it comes to the "giving to others" aspects (Colbert et al., 2016). If such appreciation and opportunities to assist others fall short, people can become demotivated and experience feelings of uselessness: they don't matter for the final product. The three self-determination factors – autonomy, competence, and relatedness – are also key factors that empirically underpin having a sense of work meaningfulness (Nikolova and Cnossen, 2020).

3.2. Robots, work meaningfulness, and self-determination

An industrial robot is a machine able to "manipulate" its environment by grasping or moving objects around it. Most of the activities that industrial robots perform are reaching and handling tasks. Examples of robots fitting this definition include manipulators that weld or paint cars, move materials and pack boxes, and load and unload workpieces from factory equipment such as Computer Numerical Control (CNC) machine tools and semiconductor fabricators. Examples of industrial equipment that are not robots include most machine tools, an assembly line conveyor belt, and a flexible manufacturing cell (Webb, 2020).

"Human" tasks overlapping with the capabilities of a robot are susceptible to automation. As industrial robots have a comparative advantage in repetitive activities and lifting heavy objects, workers with relatively routine and manual task-intensive occupations are at greater risk of replacing a large share of their tasks (Autor et al., 2003; Webb, 2020). However, due to their pre-programmed nature, industrial robots without artificial intelligence (AI) capabilities have limited ability to execute tasks in unpredictable environments, mostly those involving human contact.

Therefore, industrial robots have relatively little capacity to replace cognitive, non-routine, and interpersonal tasks. While AI technologies may substitute these tasks in the future, Webb (2020) shows that the patent texts for robotic inventions strongly overlap with relatively routine and manual occupations and little with nonroutine cognitive and interpersonal occupations.

Because robots only execute a specific set of tasks, the effect of robots on meaningfulness and self-determination is ambiguous: robots replace relatively mundane tasks, and this may allow humans to focus on new, interesting, and more complex tasks (Berg, 2019; Berg et al., 2023; Parker and Grote, 2020), increasing the potential of experiencing meaningful work. In this sense, automation could reduce unpleasant, dirty, dull, or dangerous work and free up time to pursue tasks and activities that bring freedom and fulfillment – an idea dating back at least to Karl Marx (Spencer, 2018; Spencer, 2023).

However, if the task replacement is not met with a simultaneous shift towards more purposeful activities, experiences of meaningfulness might decrease. Robots that directly replace tasks humans perform or limit task variety may reduce that person's sense of meaning. This may also occur if only minor or unimportant tasks that are no longer directly associated with the final product's success remain. Such "micro-tasks" bear little meaning in themselves, as they are not connected to a purpose or directly useful in and of themselves (Parker and Grote, 2020). Moreover, given that robots may replace certain activities and make way for others, the impact of robots on work design may strongly differ between workers in the same workplace and working in the same occupation.

Similarly, robots may also positively or negatively affect one's sense of self-determination. This strongly depends on how robots are introduced in the workplace. For instance, autonomy might decrease if one's workflow becomes dependent on the work-pace of a robot. Conversely, if workers can use the robot to their benefit, they may acquire more room for autonomous agency and discretion in developing new tasks. Likewise, one's feeling of competence may increase if relatively mundane tasks are replaced, clearing the way for more skillful tasks. However, if the robot takes over tasks that a worker takes pride in, and no challenging tasks are introduced, the feeling of competence can decrease. Lastly, if robots are seen as partners at work, one's sense of relatedness might not be compromised. And yet, relatedness can decrease if the robot affects the physical environment in such a way that personal connections are disrupted.

Barrett et al. (2012) provide an insightful case study highlighting how the introduction of a robot may affect workers differently within the same workplace. They show that the introduction of a drug-dispensing robot in a hospital pharmacy led to contrasting experiences for different workers, depending on how the robot altered their work. First, pharmacists indicated that their jobs had improved due to the increased delivery speed of medication, which provided more room for in-depth patient counseling. This made their work more interesting – appealing more strongly to their sense of competence – and more interactive, increasing their sense of relatedness to their patients.

Second, the assistants to the pharmacist, originally responsible for selecting and delivering the medications to the pharmacist, had the opposite experience. Their responsibilities diminished to the point where they were only required to load medicine onto the robot. Their sense of competence decreased, as the original expertise of knowing where to shelve which medicine was no longer necessary. Furthermore, they also experienced a decrease in autonomy, as the robot now guided where to place each item.

The third group, the technicians, had an entirely distinct experience. Before the robot was introduced, they operated similarly to the assistants. However, with the introduction of the robot, their relative position in the pharmacy changed. As the robot often stagnated and the technicians were the only workers authorized to fix the problems (even if the assistants knew how to), this increased their sense of competence and feeling of status within the organization.

These considerations lead to the following testable hypothesis:

H1. The impact of robotization on work meaningfulness and workers' sense of self-determination, encompassing autonomy, competence, and relatedness, can manifest either positively or negatively.

3.3. The moderating effect of workers' skills and demographics

As the pharmacy case study illustrates, robot adoption can significantly impact the experience of meaning and self-determination in the workplace. Some workers experience more competence as they can focus more on tasks that require their specific human capital (such as fixing the machine for the technicians), whereas others experience lower competence because the machine makes their expertise and contributions obsolete. Importantly, these changes can occur even within the same company and depend on the tasks people perform and their skills.

Therefore, we also explore the effects of several moderating variables: tasks, skill and education levels, and worker demographics. First, technology adoption (robots and ICT) generally leads to tasks being *replaced*, *augmented*, or *created* (Acemoglu and Restrepo, 2019). Individuals performing tasks comparable to those that can be taken over by technology (i.e., routine and manual tasks) are at relatively higher risk of task replacement (Autor et al., 2003; Autor, 2013; Acemoglu and Restrepo, 2019). While these workers may not face immediate unemployment, the introduction of robots that can perform some of their tasks may have implications for workers' work meaningfulness and self-determination, such as reducing the variety of tasks or the discretion over when to perform tasks. In addition, workers performing nonroutine cognitive (i.e., analytical and interpersonal) tasks face a relatively lower risk of replacement, and higher chances of task augmentation.

Therefore, we hypothesize that the nature of tasks moderates the effect of robots on the workers' perceptions of work meaningfulness and self-determination. Some of these tasks, due to their routine nature, might be more susceptible to replacement (e.g., the assistants placing the medicine in the right place). In contrast, other tasks can be enhanced by technology (e.g., the pharmacists seeing productivity increases due to faster medicine delivery) or can even lead to the emergence of entirely new tasks (e.g., the technicians working on robot maintenance).

We distinguish between two types of task characteristics that we use as moderators in our analysis. First, we observe the *routine intensity* of tasks. To capture routine tasks, we use worker-level information on repetitive tasks. Second, we have information about the nonroutine intensity of tasks, which we split into *non-routine cognitive* and *nonroutine interactive*. For the nonroutine cognitive tasks, we rely on information on whether one has to work with a computer, meaning that they are in charge of operating and working with the technology. We capture the degree of interactivity at work by utilizing information on the respondent's degree of working with clients.

Second, we conjecture that the effect of robots on meaningfulness and self-determination depends on workers' skill levels. High-skilled workers are more likely to benefit from the complementarity between human skills and machines compared with the low-skilled (Autor et al., 2003; Webb, 2020). Robots can act as complements to high-skill workers by automating only portions of routine and manual jobs, thereby increasing the value of the non-routine and cognitive tasks that these workers perform (Autor and Dorn, 2013). Therefore, we also include interactions with workers' skills to see whether these moderate the main effects. We utilize two measures of skills – one based on educational attainment and one based on the occupational category of the respondent.

Third, demographic characteristics could moderate the effects as well. Older workers might be more resistant to technological change, but on the other hand, they may be less affected by automation if they have survived past automation waves. For example, Schwabe and Castellacci (2020) show that older workers view technology as a force that does not directly threaten their careers but adds positive value to work and society. This may be because smart machines substitute for young unskilled workers but complement older skilled ones, as predicted by Sachs and Kotlikoff (2012) and empirically demonstrated by Battisti and Gravina (2021), thus possibly increasing the job quality of older workers.

We also explore whether there are gender differences in the relationship between automation and work meaningfulness and self-determination. For instance, Aksoy et al. (2021) also show that the gender pay gap increases with robotization, and medium- and high-skilled males disproportionately benefit from robot exposure. While Aksoy et al.'s (2021) results highlight differences in pay, the fact that robots predominantly increase the productivity of men suggests that the impact on their experience of meaningfulness and self-determination might also be more positive than for women.

As summarized in Table 2, these considerations form the basis of our analysis and lead to our second set of hypotheses:

H2a. Workers' tasks moderate the impact of robotization on work meaningfulness and self-determination: robotization is more likely to negatively affect those performing routine-based tasks, whereas workers with nonroutine-based tasks should be positively affected.

H2b. The work meaningfulness and self-determination of highly skilled workers and those with higher education are less likely to be negatively affected by robotization than the corresponding outcomes of low-skilled and low-educated workers.

H2c. The work meaningfulness and self-determination of older workers are less likely to be negatively affected by robotization than those of younger workers.

H2d. Female workers' work meaningfulness and self-determination are more likely to be negatively affected by robotization compared with those of male workers.

4. Data

Research regarding the consequences of automation relies on two main measures: i) industry-level data on industrial robots or ii) automation potential based on routine intensity at the occupational level capturing the risk of replaceability of tasks, regardless of whether the worker is actually exposed to that technology. An example of the latter type of measure is the Routine Task Intensity (RTI) index as used by Autor and Dorn (2013) or Acemoglu and Autor (2011), which measures the relative exposure to automation by focusing on the routine task component based on occupational descriptions of tasks from the DOT or O*NET. The main advantage of the first type of data is that it is based on the actual number of robots employed in an industry, rather than the future potential for robotization and automation. The main disadvantage is the high level of aggregation at the industry level and the inability to measure the quality of robots, just their quantity. The main advantage of the second measure is that it is available at a more granular level – e.g., two- or three-digit occupations, but the main disadvantage is that the data typically do not vary over time, are based on the US occupational dictionaries, and do not measure actual exposure to

Table 2
Possible consequences of robots on work meaningfulness and self-determination, with explanations regarding the moderators.

Experiences of	Potential positive consequences of robots	Potential negative effects of robots	Moderators of the consequences of robotization for work meaningfulness, autonomy, competence, and relatedness
Meaningfulness *(a sense of doing useful and fulfilling work)*	Robots as partners in pursuing a worthy cause, increasing efficiency and the successful completion of tasks	Robots replacing tasks, reducing personal contribution to the end goal Technology-enabled "micro-tasks" that lack meaning	**Task-based moderators** Routine intensity of tasks (repetitiveness, monotonicity, and dependency on the work pace of a machine)
Autonomy *(a sense of discretion in determining the order, speed, and methods of work)*	Increased room for job crafting and autonomous agency if human workers control robots Discretion over the development of new tasks, when old tasks are replaced	Few opportunities for job crafting due to dependence on the workflow of robot Robot control reduces opportunities for exercising judgment and agency More opportunities for management to monitor human work	Nonroutine-cognitive and -interactive intensity of tasks (working with computers and working with clients) **Skill-based moderators** Level of education Occupational skill
Competence *(a sense of having the right skills to do one's job, the ability to solve unforeseen problems, and learning new things)*	Replacing "dull, dangerous, and dirty" work with cognitively demanding tasks Creation of new tasks related to operating robots, requiring new complex skills	Increased standardization and fragmentation of tasks, requiring fewer skills Replacement of tasks makes corresponding human skills obsolete	**Individual-level moderators** Age Gender
Relatedness *(a sense of feeling helped and supported by your co-workers and supervisors)*	Robots as colleagues, capable of high-level social interaction Replacement of non-social tasks, increasing time for interpersonal contact	Workers may interpret task replacement as being personally replaceable: reducing the feeling of being appreciated Changes to the physical aspects of work that disrupt social connections	

Note: Authors' adaptation based on Smids et al. (2020) and Parker and Grote (2020).

automation, but rather automation risk.

Our paper adopts the first method of capturing automation exposure. As such, we relate the change in the stock of robots per 10,000 workers to individual-level experiences of job quality at work. We further use task-based moderators to account for the type of work people execute.

We combine information from several sources to conduct our empirical analyses and test our main propositions. First, we rely on data on the number of operational multipurpose industrial robots from the International Federation of Robotics (IFR) for each industry in each country and year. The IFR calculates robot stocks assuming a service life of 12 years, implying that the robot is out of operation after that. The IFR defines an industrial robot as an "automatically controlled, reprogrammable, multipurpose manipulator that is programmable in at least three axes, and either fixed in place or mobile and intended for and typically used in industrial automation applications" (IFR, 2021, p. 30).

We use the IFR data after 2005 because the data source has many missing values before 2005. Except for Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the UK, the IFR data only provide country totals until 2004, which other papers have dealt with by performing imputations. Furthermore, the share of the robot stock that is not classified to any particular industry also declined after 2005, making 2005 a good starting year for using IFR data (Jurkat et al., 2022). Like other studies, we had to impute the data for 2005 for Bulgaria, Greece, and Lithuania.

The denominator of the robotization variable is calculated based on the number of employed persons per industry and country in 2000 from the EUKLEMS & INTANProd database. We use the national accounts file with information on the number of workers per industry. The EUKLEMS productivity database is also the source of information on the fixed capital stock in computing, communications, computer software, and databases, underpinning our ICT control variable. We use the capital accounts data file for the ICT variable. Information for several Eastern European countries in our analysis sample is missing for the ICT variable, which is why we imputed this information based on the non-missing information from neighboring countries.

Finally, we use worker-level data from the European Working Conditions Surveys for 2010, 2015, and 2021 (Eurofound, 2022, 2023a, 2023b). The EWCS dataset contains worker-level survey answers collected via face-to-face interviews with about 1000 workers per country in 2010 and 2015. In 2021, because of the COVID-19 pandemic, the survey was conducted via the telephone, and sample sizes per country were about 1800, ranging from 1000 to 4000. To account for the question format and sampling methodology differences in the 2021 wave compared with the previous waves, we add year dummies to our regression analyses. Different workers are polled each year, and the dataset represents pooled cross-sections rather than a panel.

The EWCS dataset is very opportune for our research for several reasons. First, the surveys ask detailed questions about workers' socio-demographics and work characteristics. Importantly, the EWCS has the variables we need to construct indices of work meaningfulness, competence, autonomy, and relatedness based on the methodology in Nikolova and Cnossen (2020) and Nikolova et al. (2022). Second, the survey contains each worker's industry of employment (NACE Rev. 2, two-digit), which allows us to merge the information from the IFR and EUKLEMS with the EWCS. While the EWCS also has information on work meaningfulness and self-determination in 2005, the two-digit NACE Rev. 2 required for merging on the industry level information is only available starting in 2010. We drop individuals from the EWCS with missing industry of employment as their information cannot be merged with the rest of the data.

After merging all the information, we drop individuals with more than one job and those in the armed forces occupation. Our final merged dataset has information on individuals working in 14 industries and 20 countries in 2010, 2015, and 2021. Like most other papers using the IFR

Table 3
Constructions and variable definitions of main variables.

Variable	Explanation and coding
Dependent variables	
Meaningful work index	Index based on extracting the first component of a polychoric principal component analysis (PCA) using the following variables: (1) "your job gives you the feeling of work well done" and (2) "you have the feeling of doing useful work." The response scale is: 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Most of the time, 5 = Always. The index is standardized to have a mean of 50 and a standard deviation of 10. The index is created based on Nikolova and Cnossen (2020). Cronbach's alpha = 0.74. The first principal component has an eigenvalue of 1.69 and explains 85 % of the total variance.
Autonomy index	Index based on extracting the first component of a polychoric principal component analysis (PCA) of the following variables: (1) able to choose or change the order of tasks, (2) able to choose or change methods of work, and (3) able to choose or change speed or rate of work. Variables (1)–(3) are originally measured on a scale 0 = No, 1 = Yes. The index is standardized to have a mean of 50 and a standard deviation of 10. The index is created based on Nikolova et al. (2021). Cronbach's alpha = 0.79. The first principal component has an eigenvalue of 2.57 and explains 86 % of the total variance.
Competence index	Index based on extracting the first component of a polychoric principal component analysis (PCA) of the following variables: (1) respondent has appropriate skills to cope with current or more demanding duties, (2) main paid job involves" solving unforeseen problems on your own," (3) main paid job involves" learning new things." Variable (1) is measured as 0 = No. 1 = Yes. Variables (2)–(3) are measured on a scale, whereby 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Most of the time, 5 = Always. The index is standardized to have a mean of 50 and a standard deviation of 10. The index is created based on Nikolova and Cnossen (2020). Cronbach's alpha = 0.42. The first principal component has an eigenvalue of 1.75 and explains 58 % of the total variance.
Relatedness index	Index based on extracting the first component of a polychoric principal component analysis (PCA) using the variables: (1)" your colleagues help and support you," (2)" your manager helps and supports you." Both variables are measured on a scale, whereby 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Most of the time, 5 = Always. The index is standardized to have a mean of 50 and a standard deviation of 10. The index is created based on Nikolova and Cnossen (2020). Cronbach's alpha = 0.70. The first principal component has an eigenvalue of 1.65 and explains 83 % of the total variance.
Key independent variable	
Robotization	The inverse hyperbolic sine transformation of the change in robot stocks between year t-1 and year t-5 in each industry and country, normalized by the number of workers (in 10,000 s) in 2000 in that industry and country.
Control variables	
ICT	The inverse hyperbolic sine transformation of the change in ICT capital stocks (in computing, communications, computer software, and databases) between year t-1 and year t-5 in each industry and country, normalized by the number of workers (in 10,000 s) in 2000 in that industry and country. Missing values were imputed based on data for the neighboring countries.
Other control variables	Age (in years) split into age groups (1 = 15–35; 2 = 36–45; 3 = 45–60; 4 - over 60; 5 = missing); biological sex dummy (1 = female; 2 = male; 3 = missing information); household size (number of people in household); weekly working hours transformed into a categorical variable denoting the within-country hours quartile to which the respondent belongs. 1 = lowest quartile, 2 = second lowest quartile, 3 = third quartile, 4 = fourth quartile, 5 = missing information; education (1 = primary = early childhood education, primary education; 2 = secondary = lower secondary education, upper secondary education, and post-secondary non-tertiary education; 3 = tertiary = short-cycle tertiary education, bachelor or equivalent, master or equivalent, and doctorate or equivalent; 4 = missing information); company size indicator (1 = <250 employees, 2 >=250 employees, 3 = missing information); occupation dummies (ISCO 08 one-digit categories, including a missing category); year dummies; country dummies.

data, we exclude the "all other non-manufacturing" industry, which mostly represents services. Table 3 details the construction of the key variables used in the analyses.

4.1. Key independent variable: robotization

Our key regressor is the change in the number of robots per 10,000 workers in each industry, country, and year. Following Aksoy et al. (2021), we transformed the robotization measure using the inverse hyperbolic sine transformation (IHS). This transformation deals with the issue that the distribution of the change in robots is highly skewed. Taking the logarithm is less desirable than the IHS because the log transformation does not deal with negative numbers and zeros. Other authors in the literature have addressed the skewed distribution of the robotization variable by taking the percentile rankings of the industries (de Vries et al., 2020; Graetz and Michaels, 2018). Nevertheless, this solution is problematic because it over-emphasizes small differences between the values at the top of the distribution and under-emphasizes large differences between changes in the robotization at the bottom of the distribution (Bekhtiar et al., 2021). The IHS transformation is, therefore, preferable because it is similar to a logarithm but preserves zero and negative observations (Bellemare and Wichman, 2020). To ease the interpretation of the magnitudes of the estimated coefficient estimates, we calculate and report elasticities, where possible.

Specifically, for each industry j in country c and year t, the robotization measure R is:

$$R_{jct} = IHS\left[\frac{num.robots_{jc(t-1)}}{10,000\ employees_{jc(t=2000)}} - \frac{num.robots_{jc(t-5)}}{10,000\ employees_{jc(t=2000)}}\right] \tag{1}$$

We define robotization as a change because we are interested in technological change in terms of a "shock." We use a four-year gap to calculate the change between *t-1* and *t-5* because of the gap between the EWCS survey waves. Robotization is also lagged one year to mitigate reverse causality issues and to minimize inconsistencies in terms of when the EWCS data were collected and the reference period for the robotization stocks. We use the number of workers in 2000 in the denominator so that the changes in the robot stock are independent of changes in the number of employees. The year 2000 was selected because it predates the explosive growth in adopting robots in many countries in the sample.

4.2. Dependent variables

We utilize four dependent variables, which are all standardized composite indices with a mean of 50 and a standard deviation of 10. These indices are based on Nikolova and Cnossen (2020) and Nikolova et al. (2022). Table 3 details the concrete steps involved in constructing the variables. Our measure of autonomy deviates from that of Nikolova and Cnossen (2020) as it is based on combining only three variables (and not five) into the index. Specifically, we rely on a measure of task autonomy based on the following variables: (1) ability to choose or change the order of tasks, (2) ability to select or change methods of work, and (3) ability to choose or change speed or rate of work. Job autonomy has two interrelated aspects: i) decision-making over the work process and ii) choice over when and where to work (Parker and Grote, 2020). Our autonomy measure captures only the first aspect about having decision-making latitude about the work process. The construction of the variables is detailed in Table 3.

4.3. Control variables

We source other control variables at the individual level from the EWCS files. We create an additional "missing information" indicator for all categorical control variables to avoid omitting observations with missing information from the analyses. This additional "missing information" category has no informational value but only helps us preserve the number of observations.

The control variables include age group, biological sex, working hours, education level, private or public sector of employment, number of years with the firm (tenure), and ISCO-08 occupation (excluding the armed services), and company size.

Finally, we include the inverse hyperbolic sine transformation of changes in ICT capital (per 10,000 workers) as an additional control variable. The construction of this variable is identical to that of robotization. We want to ensure that we capture the effects of robotization on work meaningfulness and self-determination above and beyond any consequences of digitalization.

5. Methods

5.1. OLS

We explore the causal effects of robotization on work meaningfulness and self-determination using ordinary least squares (OLS) and instrumental variables techniques. Our analyses dovetail with and combine strategies explored in the extant literature (e.g., Aksoy et al., 2021; Anelli et al., 2021; Dauth et al., 2021; de Vries et al., 2020; Graetz and Michaels, 2018).

In our OLS estimations, the work meaningfulness or self-determination outcome Y of individual i, living in country c and working in industry j in survey year t is:

$$Y_{ijct} = \alpha_0 + \alpha_1 R_{jct} + \alpha_2 I_{jct} + Z_{ict}\varphi + \mu_c + \pi_t + \varepsilon_{ijct} \tag{2}$$

where R denotes ***robotization*** as detailed in Eq. (1). Furthermore, the control variables Z include age group, biological sex, working hours, education, sector of employment (public or private), number of years with the firm, and ISCO-08 occupation detailed in Section 3.3 above, I is a measure of ICT changes (constructed similarly to robotization), π_t denotes time fixed effects (a dummy variable for the 2010, 2015, or 2021 survey wave), μ_c denotes country fixed-effects, and ε_{ijct} is the stochastic error term. We use robust standard errors clustered at the country×industry level. In additional specifications (Table A3), we also report results using weights calculated with the within-country industry employment shares of hours worked (Aksoy et al., 2021; Graetz and Michaels, 2018) that provide more importance to industries with larger employment shares. Furthermore, we check whether the results are based on the differential number of worker-level observations per country available in the EWCS. To this end, we weigh all regressions using the inverse of the number of observations per country in each analysis sample in each year (Table A3).

We include time dummies (i.e., EWCS survey wave) to, at least in part, account for shocks and cyclicalities that affect countries and industries similarly in the year of the survey. Specifically, technological adoption is often pro-cyclical (Anzoategui et al., 2019; Leduc and Liu, 2023), and economic booms and busts may also affect workers' sense of work meaningfulness and self-determination. Of course, we cannot perfectly capture all cyclical effects given the frequency of our data, but the inclusion of the time dummies should account for some of these influences, as well as differences in the survey mode. Furthermore, country-specific fixed effects account for different institutional and cultural features across countries, including cultural interpretation of the underlying self-reported work quality, as well as slow-changing institutions and labor market regulations.

5.2. Instrumental variables

The two main challenges of estimating causal effects with Eq. (2) are omitted variables bias and sorting of workers into industries. First, there may be omitted industry-specific shocks that are correlated with both the pace of adopting automation and also affect the way that individuals perceive their work meaningfulness and can derive autonomy, competence, and relatedness from their jobs. Second, workers with particular unobservable traits may be more likely to choose jobs that are more or less likely to be automated.

We mitigate these issues by relying on instrumental variables techniques. Like Anelli et al. (2021), our main instrument is based on the industry adoption of robotization in all other countries in the sample except the respondent's, which is similar to the instrument used in Acemoglu and Restrepo (2020). The logic of this instrument is that we are trying to capture the industry-specific trends in innovation and technological progress that are common across all countries. The instrument deals well with the first source of endogeneity outlined above as well as with self-selection. We also include relevant control variables to mitigate selection issues and offer several sensitivity checks.

This instrument relies on the untestable assumption the industry level of robotization in other countries is independent of the respondents' work meaningfulness and self-determination. The instrument would be invalid if it correlates with unobserved shocks that are common across all countries and industries and cause all industries to undertake robotization.[4]

The cross-country literature on automation has mostly relied on two instruments proposed by Graetz and Michaels (2018), i.e., the so-called "replaceable hours" and "robot arms" instruments (see, for example, Aksoy et al., 2021 and de Vries et al., 2020). The first instrument captures the share of the industry's employment hours performed in occupations that are potentially replaceable by robots from the viewpoint of the task descriptions of occupations in the 1980s in the US. The second instrument captures the extent to which US industries in 1980 contained occupations with reaching and handling tasks relative to other physical tasks.

These instruments have several limitations, as discussed in, for example, de Vries et al. (2020). The variables are based on the US's industrial structure and may capture trends and developments across industries that correlate with other changes over time (e.g., globalization). More fundamentally, these instruments have recently come under attack because they violate the monotonicity assumption. Specifically, the first-stage results show implausible correlations when we split the data into the manufacturing and non-manufacturing sectors, a problem described in Bekhtiar et al. (2021). Nevertheless, for completeness and transparency, we present the results with these instruments (Table A2), though we advise readers to exercise caution.

While the instrument of the industry-level adoption of automation in all other countries except the respondent's is not a silver bullet, its performance in the first-stage regressions and associated diagnostic tests seem reasonable. The IV results are also qualitatively in line with the OLS results, though the magnitudes of the coefficient estimates are higher with the IV than with the OLS results, which is plausible.

Our goal is not to argue about the superiority of one set of instruments over another or claim that we resolve all endogeneity concerns. Rather, it is to provide plausibly causal estimates and compare and contrast the performance of OLS vs. the 2SLS, while also providing additional robustness checks.

5.3. Exploring heterogeneity

We empirically test whether workers performing different tasks differentially experience self-determination and work meaningfulness by interacting the tasks with robotization, following from H2a-H2d. We focus on three tasks: i) repetitive tasks ii) working with computers, and iii) social tasks.[5]

$$Y_{ijct} = \alpha_0 + \alpha_1 R_{jct} + \beta_\tau \tau_{ijct} + \gamma_\tau R_{jct} {}^* \tau_{ijct} + \alpha_2 I_{jct} + Z_{ict}\varphi + \mu_c + \pi_t + \varepsilon_{ijct} \quad (3)$$

In Eq. (3), the coefficient estimates γ_τ allow us to explore whether robotization differentially affects the work meaningfulness and self-determination of people working in jobs requiring different tasks. We estimate Eq. (3) based on the IV strategy using the 2SLS estimator.

Furthermore, we explore whether workers in different parts of the skills distribution and of different ages and genders differentially experience meaningfulness and self-determination. Specifically, we anticipate that automation may lead to de-skilling and therefore worsen the work meaningfulness and self-determination experiences of low-skilled workers while providing high-skilled workers with the opportunity to shift to new and creative tasks. In this instance, τ_{ijct} indicates skill levels (high, medium, and low).

We operationalize skills by education (i.e., primary, secondary, and tertiary) and by grouping 1-digit ISCO occupations into high-, medium-, and low-skilled based on the ILO definitions. Specifically, we classify managers, professionals, technicians and associate professionals as high-skilled; clerical support workers, service and sales workers, skilled agricultural, forestry, and fishery workers as "medium-skilled" workers; and craft and related trades workers, plant and machine operators, and assemblers, and elementary occupations as "low-skilled". The analyses by age and gender are performed analogously to those with tasks and skill levels.

6. Results

6.1. Descriptive statistics

Fig. 1 depicts the average number of robots per 10,000 workers for the years 2005, 2009, 2010, 2014, 2016, and 2020. Given our empirical setup, our measures of robotization refer to changes in the number of robots per 10,000 workers between 2005 and 2009 (for EWCS observations in survey wave 2010), 2010–2014 (for EWCS observations in survey wave 2015), and 2016–2020 (for the 2021 EWCS). Industrial robots are most prevalent in the automotive industry (e.g., 629 robots per 10,000 workers in 2020) and least widespread in the electricity, gas, water supply, construction, and education/research industries.

During the 2005–2020 period, the average increase in robotization across all industries was 389 %, with the mining and quarrying industry realizing a change of 2601 %, followed by growth of 689 % in the industrial machinery sector, and 475 % in the electricity, gas, and water supply. These are all industries that started with relatively low levels of robots in 2005, which explains these high increases (See Table A1).

Figs. 2–5 detail the development of work meaningfulness and self-determination variables over the analysis period. The key takeaway from these figures is that the changes in the dependent variables tend to be rather modest both within industries and over time.

Table 4 provides summary statistics for the analysis samples for each dependent variable. Because those who work alone did not answer the relatedness questions, the analysis sample for relatedness is smaller than for the other dependent variables. In addition, the competence questions were not asked in the 2021 survey. Table A9 also details the sample composition for the work meaningfulness sample across the 2010, 2015, and 2021 survey waves. The 2021 sample contains a much larger share of individuals with tertiary education (0.54 in 2021 compared with roughly 0.3 in 2010 and 2015), which is because these respondents were easier to reach during the pandemic (Ipsos, 2022).

[4] Moreover, workers sort into industries and jobs offering different opportunities for meaningfulness and self-determination because they have particular unobserved traits, such as motivation or particular preferences for work meaningfulness and job quality. The IV strategy also deals with this problem. We include individual-level controls to mitigate this issue.

[5] In a working paper version of this manuscript, which only relied on the 2010 and 2015 EWCS waves, we also reported heterogeneity by dependence on the work pace of a machine and performing monotonous tasks. Unfortunately, these heterogeneity analyses are not possible with the 2021 EWCS as these questions were not asked then.

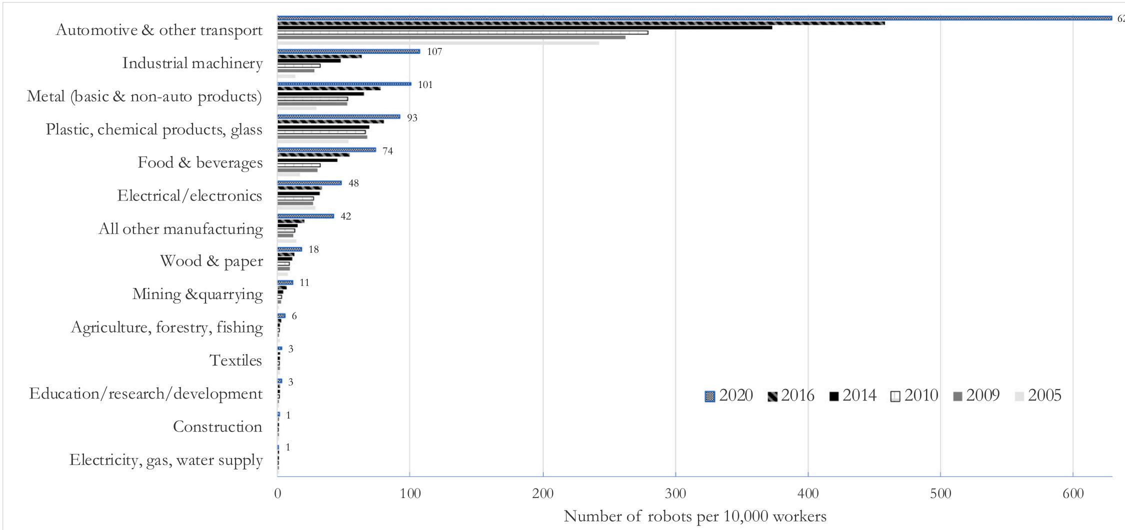

Fig. 1. Industrial robots per 10,000 workers by industry and year, 2005–2020.
Source: Authors' calculations based on IFR and EUKLEMS.
Notes: The figure shows the average robot density (robot stock per 10,000 workers) by industry for 2005, 2009, 2010, 2014, 2016, and 2020 and sorted by the robot density in 2020. The values for 2020 are shown next to each bar. The industries Construction, Education/research/development, and Electricity, gas, and water supply have very small non-zero values.

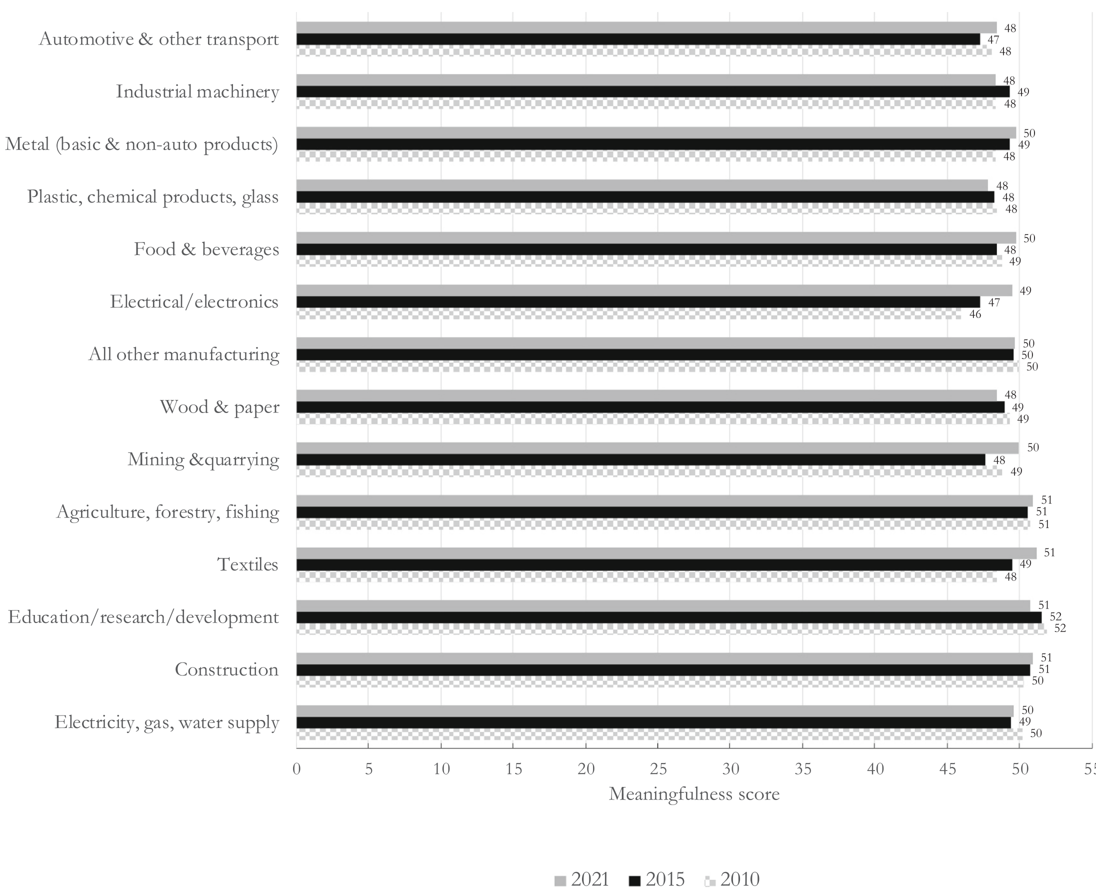

Fig. 2. Work meaningfulness, by industry and year.
Source: Authors' calculations based on the European Working Conditions Surveys (2010, 2015, 2021).
Notes: The figure shows the average work meaningfulness by industry for 2010, 2015, and 2021, sorted by the robot density in 2020 as in Fig. 1. Work meaningfulness is standardized to have a mean of 50 and a standard deviation of 10.

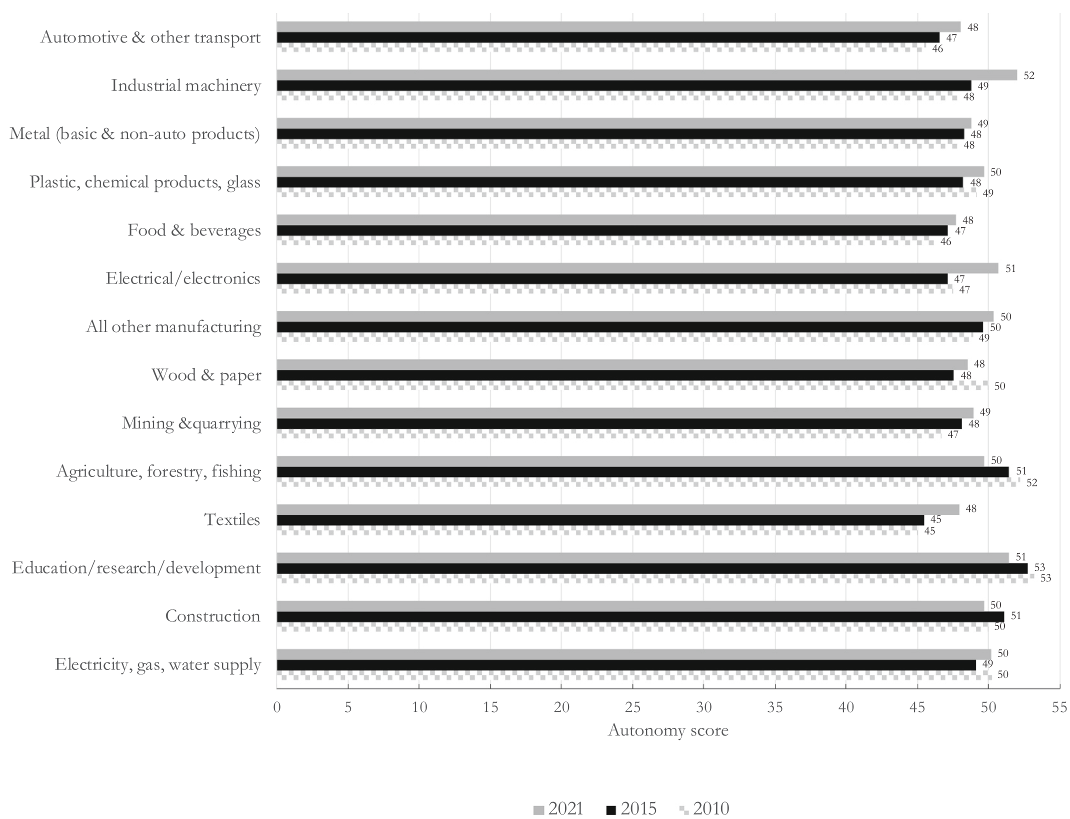

Fig. 3. Autonomy, by industry and year.
Source: Authors' calculations based on the European Working Conditions Surveys (2010, 2015, 2021).
Notes: The figure shows the average autonomy levels by industry for the years 2010, 2015, and 2021, sorted by the robot density in 2020 as in Fig. 1. Autonomy is standardized to have a mean of 50 and a standard deviation of 10.

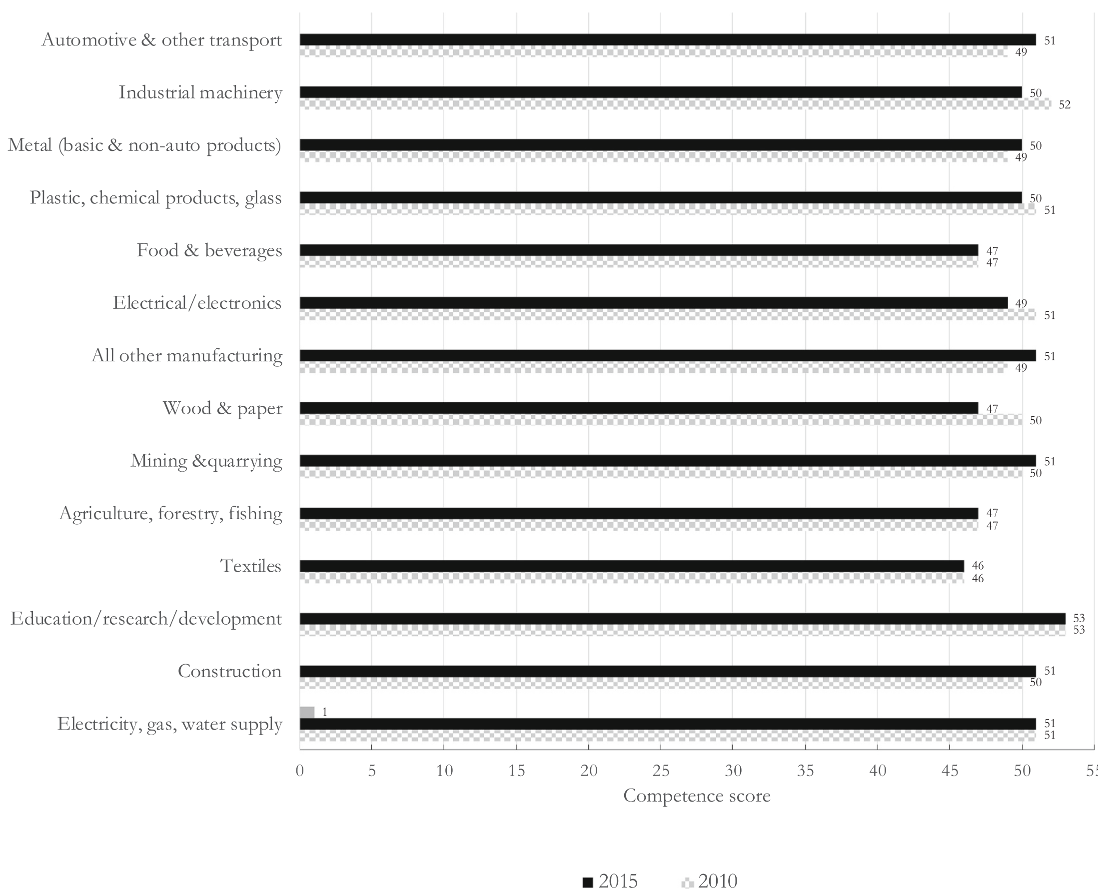

Fig. 4. Competence, by industry and year.
Source: Authors' calculations based on the European Working Conditions Surveys (2010, 2015, 2021).
Notes: The figure shows the average competence levels by industry for the years 2010 and 2015, sorted by the robot density in 2020 as in Fig. 1. Competence is standardized to have a mean of 50 and a standard deviation of 10. There is no information about the underlying variables comprising the competence index in the 2021 EWCS survey.

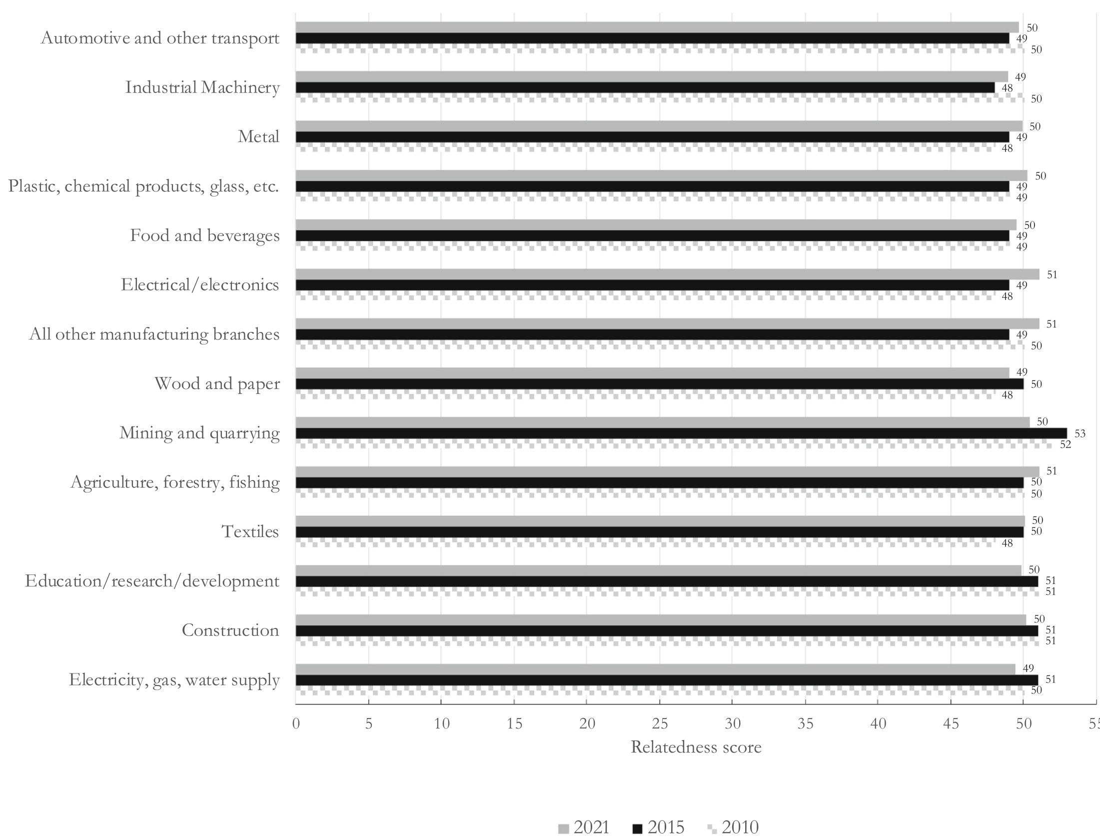

Fig. 5. Relatedness, by industry and year.
Source: Authors' calculations based on the European Working Conditions Surveys (2010, 2015, 2021).
Notes: The figure shows the average relatedness levels by industry for the years 2010, 2015, and 2021, sorted by the robot density in 2020 as in Fig. 1. Relatedness is standardized to have a mean of 50 and a standard deviation of 10.

Table 4
Summary statistics.

	Work meaningfulness sample, $N = 26{,}083$		Autonomy sample, N = 26,039		Competence sample, $N = 16{,}578$		Relatedness sample, $N = 21{,}651$	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Robotization	1.041	1.808	1.034	1.815	0.767	1.726	1.119	1.869
ICT adoption	1.835	2.350	1.818	2.349	1.725	2.136	1.912	2.386
Age group								
15–35	0.268	0.443	0.268	0.443	0.253	0.435	0.284	0.451
36–45	0.275	0.447	0.276	0.447	0.275	0.447	0.278	0.448
45–60	0.387	0.487	0.386	0.487	0.399	0.490	0.383	0.486
Over 60	0.067	0.250	0.067	0.251	0.068	0.252	0.052	0.222
Missing information	0.003	0.056	0.003	0.059	0.004	0.063	0.003	0.052
Biological sex								
Female	0.406	0.491	0.408	0.491	0.402	0.490	0.428	0.495
Male	0.593	0.491	0.591	0.492	0.598	0.490	0.571	0.495
Missing information	0.001	0.033	0.001	0.032	0.000	0.011	0.001	0.033
Working hours quartile								
1st	0.432	0.495	0.432	0.495	0.435	0.496	0.457	0.498
2nd	0.188	0.391	0.187	0.390	0.195	0.396	0.206	0.404
3rd	0.139	0.346	0.138	0.345	0.139	0.346	0.148	0.355
4th	0.210	0.407	0.213	0.409	0.203	0.402	0.169	0.375
Missing information	0.031	0.173	0.030	0.171	0.028	0.165	0.020	0.139
Education								
Primary	0.043	0.202	0.043	0.204	0.057	0.232	0.033	0.177
Secondary	0.567	0.495	0.569	0.495	0.641	0.480	0.555	0.497
Tertiary	0.386	0.487	0.383	0.486	0.299	0.458	0.408	0.492
Missing information	0.004	0.061	0.004	0.062	0.003	0.055	0.004	0.061
Occupation								
Managers	0.078	0.269	0.078	0.269	0.057	0.232	0.065	0.246
Professionals	0.250	0.433	0.248	0.432	0.204	0.403	0.278	0.448
Technicians and associate professionals	0.099	0.298	0.098	0.298	0.084	0.277	0.110	0.313
Clerical support workers	0.061	0.240	0.061	0.239	0.058	0.234	0.069	0.253
Service and sales workers	0.044	0.205	0.044	0.205	0.049	0.216	0.046	0.210
Skilled agricultural, forestry, and fisheries workers	0.054	0.226	0.055	0.228	0.070	0.256	0.015	0.123
Craft and related trades workers	0.241	0.428	0.241	0.428	0.272	0.445	0.229	0.420
Plant and machine operators, and assemblers	0.096	0.294	0.096	0.295	0.109	0.311	0.109	0.312
Elementary occupations	0.076	0.265	0.077	0.266	0.094	0.291	0.079	0.269
Unknown occupation	0.001	0.039	0.001	0.039	0.002	0.048	0.001	0.035
Company size								
<250 workers	0.831	0.375	0.834	0.372	0.854	0.353	0.807	0.394
250 workers and more	0.145	0.352	0.142	0.349	0.124	0.329	0.167	0.373
Missing information	0.024	0.153	0.024	0.154	0.023	0.149	0.026	0.159
Tenure								
Less than 1 year	0.106	0.308	0.107	0.309	0.131	0.337	0.112	0.315
1–5 years	0.264	0.441	0.267	0.443	0.256	0.436	0.279	0.449
More than 5 years	0.577	0.494	0.575	0.494	0.595	0.491	0.560	0.496
Missing information	0.052	0.223	0.050	0.219	0.019	0.135	0.049	0.215
Employee type								
Private employee	0.750	0.433	0.753	0.431	0.766	0.423	0.715	0.451
Public employee	0.241	0.428	0.239	0.426	0.228	0.420	0.277	0.447
Missing information	0.009	0.093	0.008	0.090	0.005	0.072	0.008	0.090

Notes: The table denotes the summary statistics for the key variables used in the regression analyses. Variable definitions are available in Table 3. Data on competence is available only for 2010 and 2015. Relatedness questions are not asked to those who work alone.
Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021).

6.2. Main results based on OLS and IV estimations

Table 5 details our main results regarding the relationship between robotization, work meaningfulness, and self-determination. Panel A reports OLS estimates. Panels B and C feature the second and first stages of the 2SLS estimates, respectively.

Our OLS in Panel A results suggest that robotization is negatively associated with work meaningfulness, autonomy, competence, and relatedness, with the latter association being statistically insignificant.

The IV estimates also corroborate this conclusion. The second-stage results (Panel B) further confirm the negative relationship between robotization, work meaningfulness, and self-determination. The coefficient estimates in Panel B are larger than the OLS ones and relatedness is now statistically significant at the 5 % level, suggesting that the OLS estimates are likely affected by endogeneity that leads to underestimating the impact of robotization on the well-being outcomes we study. The coefficient estimates from the first-stage regressions (Panel C) show that our instrument is good at predicting robotization. The *F*-statistic ranges from 80 to 262, which suggests that our instrument is strong.

At first sight, the elasticity estimates appear rather small. For example, doubling robotization corresponds to a 0.9 % decline in work meaningfulness, a 1 % drop in autonomy, a 0.7 % decline in competence, and a 0.3 % drop in relatedness, based on the elasticities in Panel B.

To put these results in perspective, we illustrate their significance by using the robotization levels of two industries – the food and beverages (74 robots per 10,000 workers) and the automotive industry (629 robots per 10,000 workers) in 2020. Should robot adoption in the food and beverage industry increase to match that of the automotive industry (representing a 7.5-fold increase in robotization), we estimate a 6.8 % (750*0.009) decrease in work meaningfulness and 7.5 % (750*0.010) decrease in autonomy, as well as a 5.3 % (750*0.007) drop in competence and a 2.3 % fall in relatedness (based on the elasticities reported below our IV estimations in Table 5, Panel B). Our calculations are based

Table 5
The effect of robotization on work meaningfulness, autonomy, competence, and relatedness.

	(1)	(2)	(3)	(4)
	Panel A: Ordinary Least Squares			
	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	−0.252***	−0.177***	−0.128**	−0.043
	(0.042)	(0.052)	(0.058)	(0.056)
Elasticity	−0.005	−0.004	−0.003	−0.001
R^2	0.054	0.141	0.192	0.046
	Panel B: IV Peer Robot Adoption Second Stage			
	Work meaningfulness	Autonomy	Competence	Relatedness
Robotization	−0.447***	−0.515***	−0.346***	−0.162**
	(0.085)	(0.082)	(0.128)	(0.080)
Elasticity	−0.009	−0.010	−0.007	−0.003
R^2	0.053	0.138	0.191	0.045
	Panel C: IV Peer Robot Adoption First Stage			
	Robotization	Robotization	Robotization	Robotization
Peer robot adoption	0.680***	0.677***	0.578***	0.677***
	(0.042)	(0.043)	(0.065)	(0.043)
1st stage F-stat	261.5	249.5	79.51	242.9
Number of observations	26,083	26,039	16,578	21,651

Notes: The table reports results from OLS (Panel A) and IV (Panel B) regressions of work meaningfulness, autonomy, competence, and relatedness on robotization. The first stage results are reported in Panel C. Robotization is measured as the inverse hyperbolic sine transformation of the change in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, number of years with the company, public/private sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the country×industry level. All dependent variables are standardized to have a mean of 50 and standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

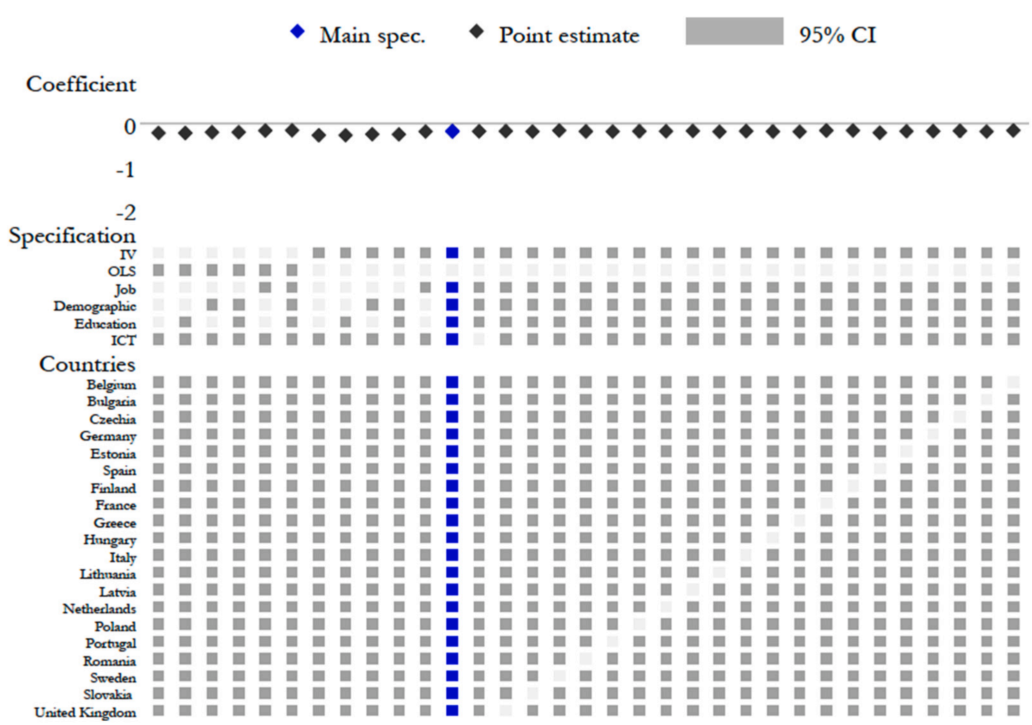

Fig. 6. Specification curve analysis, work meaningfulness.
Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021).
Notes: The figure shows the specification curve analysis for work meaningfulness as the dependent variable and different estimations of Eq. (2). The main specification is the one from Table 5, Panel B, Model (1). Work meaningfulness is standardized to have a mean of 50 and a standard deviation of 10.

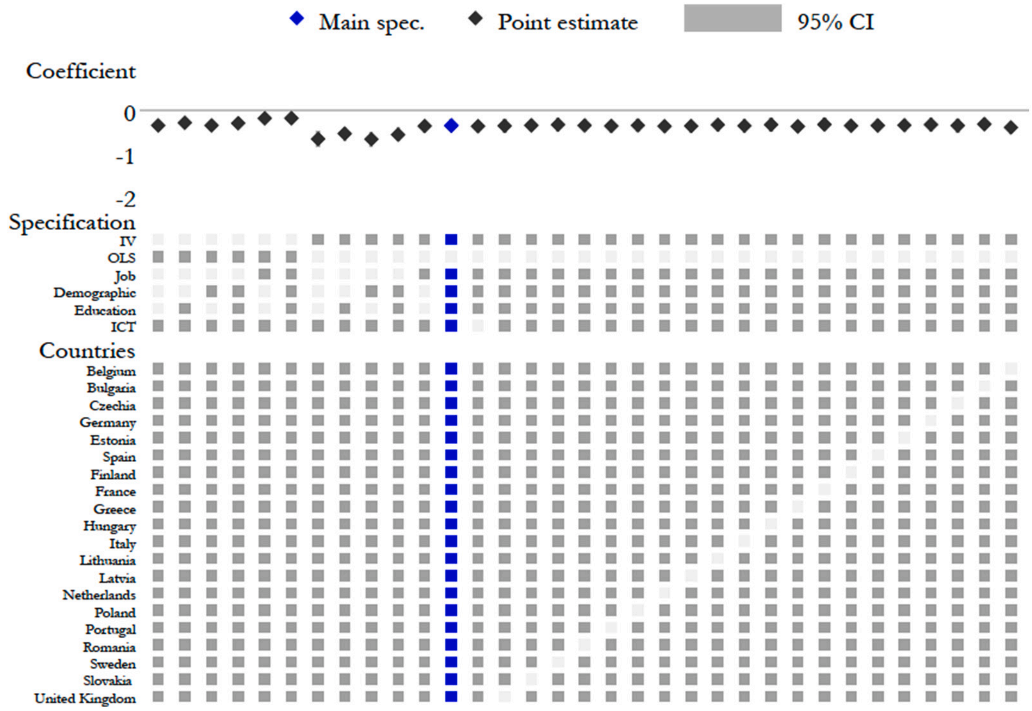

Fig. 7. Specification curve analysis, autonomy.
Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)
Notes: The figure shows the specification curve analysis for autonomy as the dependent variable and different estimations of Eq. (2). The main specification is the one from Table 5, Panel B, Model (2). Autonomy is standardized to have a mean of 50 and a standard deviation of 10.

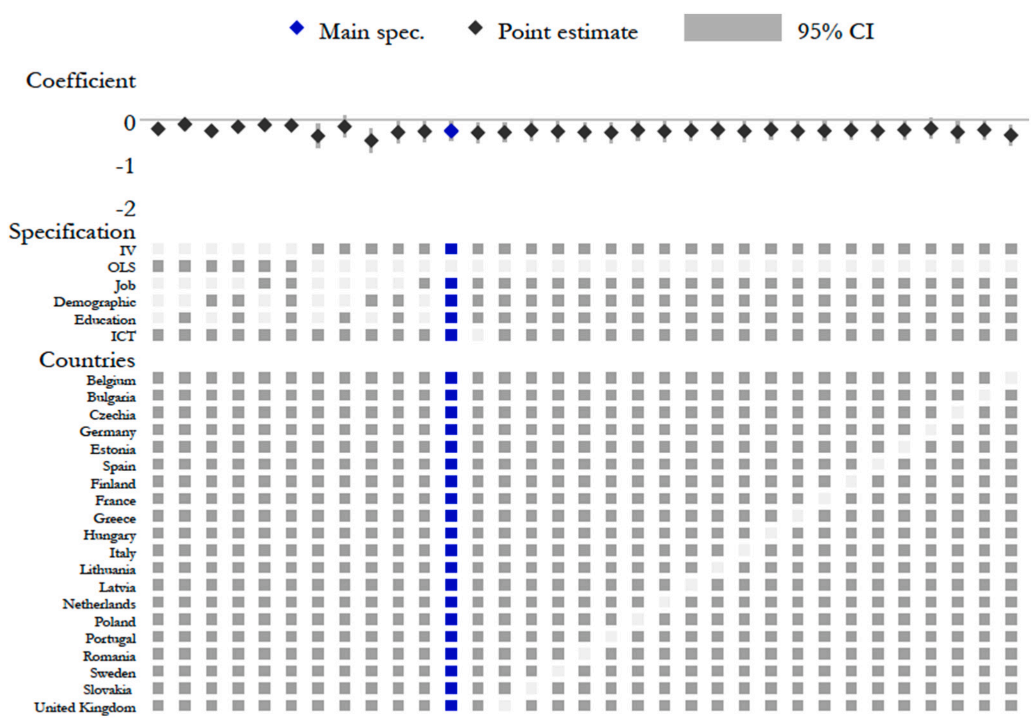

Fig. 8. Specification curve analysis, competence.
Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021).
Notes: The figure shows the specification curve analysis for competence as the dependent variable and different estimations of Eq. (2). The main specification is the one from Table 5, Panel B, Model (3). Competence is standardized to have a mean of 50 and a standard deviation of 10.

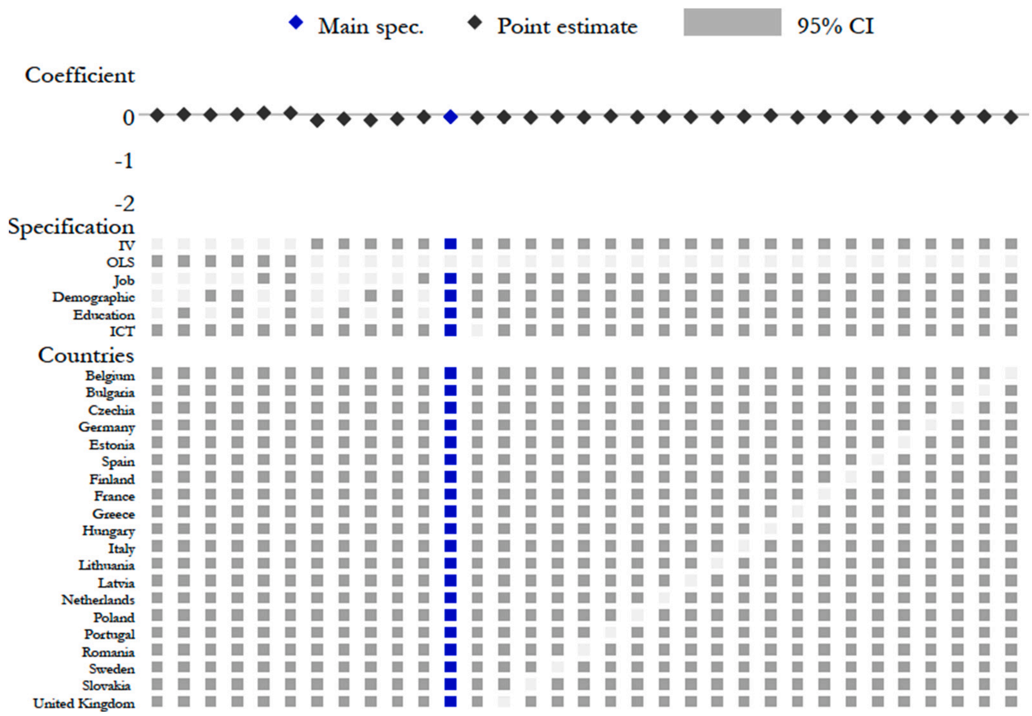

Fig. 9. Specification curve analysis, relatedness.
Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021).
Notes: The figure shows the specification curve analysis for relatedness as the dependent variable and different estimations of Eq. (2). The main specification is the one from Table 5, Panel B, Model (4). Relatedness is standardized to have a mean of 50 and a standard deviation of 10.

on a move from a top 5 to a top 1 industry regarding robot adoption levels in 2020 (see Table A1). Based on the EUKLEMS data, in 2020, nearly 4.5 million individuals worked in the food and beverages industry and about 3.3 million in the automotive industry across the countries in our study. Therefore, the impact sizes we document may seem small in isolation, but given the large number of employees affected in such sizable industries, the overall effect could be substantial.[6]

Moreover, if we extrapolate these calculations to less automated industries such as agriculture, the effect sizes become even more pronounced. An increase from the robot adoption levels in agriculture in 2020 (roughly 6 robots per 10,000 workers) to the levels in Plastic, chemical products, and glass (93 robots per 10,000 workers) (a 14.5-fold increase) could result in a 13 % drop in work meaningfulness and a 14.5 % drop in autonomy. We note that this is a shift from the top 10 industry to the top 4 industry in terms of robot adoption in 2020.

The substantial surge in robot adoption within various industries during our study period, especially among those industries with previously low levels of robot adoption, entails large consequences for meaningfulness and autonomy. The average percentage change in the industries we studied across the 2005–2020 time period was 389 %. This change suggests that the average loss of meaningfulness and autonomy for a typical worker in our sample would be around 3.5 % (0.009*389) and 4 % (0.010*389), respectively.

Therefore, the main conclusion from Table 5 is that robotization hurts work meaningfulness and self-determination, and the consequences may appear modest but are economically significant. Therefore, we show support for Hypothesis 1 in the sense that we find a negative and statistically significant relationship between robotization and our outcome variables.

6.3. Robustness checks

We offer a battery of sensitivity checks. First, using specification curve analyses (Simonsohn et al., 2020), we investigate whether our results are robust to using different sub-samples and modifications of Eq. (2). The main logic of the specification curve analyses is to re-estimate Eq. (2) with alternative control variables (e.g., including and excluding the ICT control, including and excluding demographic variables, education, and job controls), estimating the equation using OLS or an IV, and excluding one country at a time from the analysis sample. We provide such specification charts for all four dependent variables. We then graphically present the distribution of the estimates and their confidence intervals in Figs. 6–9.

All estimates we detail in those figures include country and year fixed effects but differ based on the estimator and the included covariates and countries. Specifically, we present the first set of estimates based on OLS estimations – first only including the ICT control in addition to the country and year fixed effects. We then sequentially include education variables, demographic variables, job characteristics, or only education and demographic variables, and finally, all possible controls. We then show different variations of the IV specifications. The baseline IV estimates from Table 5, Panel B, are highlighted in blue. We sequentially include different sets of control variables and exclude one country at a time from the regression models. Figs. 6–9 detail that the results in Table 5 are consistent across different specifications and modifications of Eq. (2).

In addition, we check whether the results are robust to using the replaceable hours and robotic arms instruments from Graetz and Michaels (2018), which we offer for completeness in Table A2. As we explain in Section 4.2 above, these instruments are less desirable than

[6] Another way to think of the 6.8 % decline in work meaningfulness is in terms of switching from the education/research/and development industry in 2021, where workers had an average work meaningfulness score of 51 to the automobile industry in 2021, where work meaningfulness in 2021 was 48. Therefore, a 7.5 fold-increase in robotization is like switching from a high-meaning industry like education and research to the automobile industry in terms of the loss in meaning it generates.

Table 6
The moderating effects of tasks for the relationship between robotization and work, meaningfulness, autonomy, competence, and relatedness.

	(1) Work meaningfulness	(2) Autonomy	(3) Competence	(4) Relatedness
Panel A: The moderating effect of individual-level repetitive tasks, IV regressions second stage				
Robotization	−0.383***	−0.150	−0.014	−0.002
	(0.135)	(0.118)	(0.182)	(0.102)
Repetitive tasks	−0.644***	0.162	0.241	−0.609***
	(0.214)	(0.232)	(0.233)	(0.223)
Robotization×Repetitive tasks	−0.083	−0.714***	−0.469**	−0.246**
	(0.150)	(0.141)	(0.182)	(0.117)
R^2	0.059	0.146	0.191	0.047
1st stage F-stat	89.72	85.44	37.66	118.8
Number of observations	21,240	21,232	16,533	21,595
Panel B: The moderating effect of working with computers, IV regressions second stage				
Robotization	−0.428***	−1.287***	−0.942***	−0.388***
	(0.123)	(0.144)	(0.176)	(0.113)
Working with computers	1.094***	2.910***	2.712***	0.393**
	(0.149)	(0.190)	(0.192)	(0.159)
Robotization×Working with computers	0.062	1.474***	1.604***	0.392***
	(0.120)	(0.140)	(0.198)	(0.110)
R^2	0.056	0.159	0.209	0.046
1st stage F-stat	109	109.6	39.26	106
Number of observations	25,998	25,957	16,512	21,593
Panel C: The moderating effect of social tasks, IV regressions second stage				
Robotization	−0.247**	−0.457***	−0.083	−0.189*
	(0.113)	(0.113)	(0.161)	(0.104)
Working with clients	1.431***	2.871***	3.029***	0.309
	(0.215)	(0.261)	(0.248)	(0.209)
Robotization×Working with clients	−0.307**	0.205	−0.251	0.110
	(0.124)	(0.134)	(0.183)	(0.128)
R^2	0.055	0.158	0.207	0.046
1st stage F-stat	125	119	37.10	118.4
Number of observations	26,020	25,976	16,527	21,605

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization, by whether the respondent performs repetitive hand or arm movements (Panel A), by whether the respondent works with a computer (Panel B), and by whether the respondent performs social tasks (dealing directly with people who are not employees at the respondent's workplace, such as customers, passengers, pupils, or patients) (Panel C). Robotization is measured as the inverse hyperbolic sine transformation of the change in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, the number of years with the company, public/private sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the country×industry level. All dependent variables are standardized to have a mean of 50 and standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.
Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021)

the instrument we utilize in the main specifications. The results remain in line with the those in Table 5.

Table A3 investigates whether the effects we estimate are robust to different weighting schemes. In Panel A of Table A3, we use the country-specific industry employment shares as Graetz and Michaels (2018) and Aksoy et al. (2021), which puts more importance on larger industries. Furthermore, in Panel B of Table A3, we check whether the results are driven by countries with a larger number of observations by weighting all regressions using the inverse of the number of observations in each country and year as a weight. The results support our conclusions from our estimations in Table 5.

Furthermore, Table A4 offers a robustness check where we include country×year fixed effects, which control for shocks and omitted factors that differentially affect countries across time (e.g., globalization, country-specific natural disasters, or technological breakthroughs in particular countries). In Panel B, we also add an offshorability control, which is at the industry level and sourced from Graetz and Michaels (2018). The results largely align with our main findings, though the evidence for competence and relatedness is less robust, being insignificant for relatedness, and marginally statically significant in Panel B for competence, which is why we put less emphasis on these outcomes in the paper.

Finally, Table A5 checks whether our results differ based on workers' job tenure (number of years in the same company). Specifically, our results may be driven by the self-selection of workers into industries that have become automated, or particular workers may be self-selecting into staying in given industries. While IV in principle deal with these concerns, our sample only includes employed people who have not lost their jobs due to robotization. This implies that those individuals may have largely adjusted to their new circumstances. While testing the adaptation explanation requires panel data on the same workers over time, our results suggest that our findings do not differ among people who just started the job compared to those with longer tenure (Table A5). This suggests that adaptation may not be the main driver of our findings, as workers who have been in the company for a long time do not experience automation differently than the newcomers.

7. Heterogeneity

We next turn to the tests of Hypotheses H2a-H2d. The results of our

Table 7
The moderating effects of skills for the relationship between robotization and work, meaningfulness, autonomy, competence, and relatedness.

	(1)	(2)	(3)	(4)
	Work meaningfulness	Autonomy	Competence	Relatedness
Panel A: The moderating effect of skill levels (education), IV regressions second stage				
Robotization	−0.381***	−0.657***	−0.364**	−0.234**
	(0.105)	(0.102)	(0.146)	(0.100)
Tertiary education	−0.184	1.337***	2.330***	−0.055
	(0.271)	(0.241)	(0.291)	(0.275)
Robotization×Tertiary Education	−0.282*	0.475***	−0.042	0.187
	(0.152)	(0.114)	(0.240)	(0.139)
R^2	0.050	0.135	0.188	0.045
1st stage F-stat	121.2	120	31.29	121
Number of observations	25,984	25,940	16,528	21,570
Panel B: The moderating effect of skill levels (based on ILO classification), IV regressions second stage				
Robotization	−0.430***	−0.915***	−0.387*	−0.184
	(0.138)	(0.133)	(0.197)	(0.120)
High Skilled	1.659***	4.371***	5.216***	1.069***
	(0.374)	(0.285)	(0.431)	(0.309)
Medium Skilled	1.201***	3.940***	1.377***	0.760*
	(0.342)	(0.472)	(0.398)	(0.397)
Robotization×High Skilled	−0.129	0.755***	0.056	0.044
	(0.187)	(0.149)	(0.293)	(0.152)
Robotization×Medium Skilled	−0.304	0.173	0.019	−0.135
	(0.195)	(0.244)	(0.280)	(0.208)
R^2	0.041	0.117	0.164	0.042
1st stage F-stat	74.69	72.87	28.91	70.50
Number of observations	26,001	25,958	16,498	21,586
Panel C: The moderating effect of age, IV regressions second stage				
Robotization	−0.507***	−0.450***	−0.388***	−0.138
	(0.091)	(0.088)	(0.138)	(0.089)
Aged 50 and older	1.383***	0.573***	−0.961***	−0.778***
	(0.184)	(0.204)	(0.240)	(0.181)
Robotization×Aged 50 and older	0.089	−0.227*	0.037	−0.107
	(0.113)	(0.122)	(0.185)	(0.122)
R^2	0.048	0.135	0.186	0.043
1st stage F-stat	134.3	130	42.04	127.2
Number of observations	26,001	25,949	16,512	21,593
Panel D: The moderating effect of gender, IV regressions second stage				
Robotization	−0.395***	−0.572***	−0.733***	−0.102
	(0.123)	(0.127)	(0.199)	(0.125)
Male	−0.006	0.937***	0.826***	0.284
	(0.242)	(0.230)	(0.256)	(0.262)
Robotization×Male	−0.120	0.084	0.519***	−0.103
	(0.127)	(0.122)	(0.189)	(0.140)
R^2	0.051	0.136	0.188	0.045
1st stage F-stat	134.6	122.5	41.02	124.4
Number of observations	26,055	26,013	16,576	21,627

Notes: The table reports results from IV regressions of work meaningfulness, autonomy, competence, and relatedness on robotization, by the respondent's education level (Panel A), skill level (Panel B), the respondents' age (Panel C), and by the respondent's gender (Panel D). Robotization is measured as the inverse hyperbolic sine transformation of the change in the number of robots per 10,000 workers. All regressions include a constant and country and year fixed effects, and the following demographic and job controls: age group, gender, hours of work, education, occupation, company size, number of years with the company, private/public sector, and the inverse hyperbolic sine transformation of changes in ICT capital. All regressions include standard errors clustered at the country×industry level. All dependent variables are standardized to have a mean of 50 and standard deviation of 10. By construction, the relatedness index excludes individuals who work alone. The instrumental variable is based on the industry adoption of robots in all other countries in the sample (except that particular country). The analysis sample is based on 20 European countries and 14 industries. See Table 3 for variable definitions.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Source: Authors' calculations based on IFR, EUKLEMS, and European Working Conditions Surveys (2010, 2015, 2021).

heterogeneity analyses based on the type of tasks, skills, and socio-demographic characteristics are presented in Tables 6 and 7, respectively.

Tables 6–7 demonstrate that robotization's effect on work meaningfulness does not differ much based on the respondent's task content, skills, or demographics. This suggests that the negative effect of robotization on work meaningfulness is independent of workers' tasks, skills, age, and gender. These findings could imply that people do not derive meaning directly from the content of their tasks in the context of robotization, but from the individual goals they pursue by doing these tasks that imbue their work with meaning.

Furthermore, we find that having a routine role drives the negative impact of robotization on autonomy, competence, and relatedness (Models (2)–(4) in Panel A of Table 6). This may be because robotization furnishes fewer opportunities for job crafting and problem-solving, and in the presence of routine tasks, leaves even fewer tasks requiring judgment and agency in the work process. Furthermore, workers with routine tasks may have less time to socialize with their colleagues after robots are introduced. This is in line with the insights from the Barrett et al. (2012) pharmacy case study, as well as the broader literature documenting the negative impacts of technology on workers executing routine tasks (e.g., Acemoglu and Autor, 2011).

Conversely, those working with computers (Panel B of Table 6) — which we interpret as being in control of the workflow of technology by operating it— can completely offset the negative impact of robotization on autonomy, competence, and relatedness (but not work meaningfulness). Yet, working with clients (Panel C of Table 6) in robot-intensive industries does not offset or alter the negative effects of robotization on autonomy or any of the other outcomes we study.

When exploring skills' moderating effect on the relationship between robotization and work meaningfulness and self-determination, we perform two separate regressions—based on the education (primary, secondary, and tertiary) and skill level (low-, medium-, and high-skilled). Higher education seems to cushion the negative effects of robotization on autonomy (Panel A of Table 7). This finding is unsurprising: those with higher education can enjoy more autonomy due to robots' introduction in the workplace, as they may outsource some tasks to the machines, giving them the freedom to focus on developing new ones. Beyond that, robotization negatively and similarly impacts respondents' work meaningfulness, competence, and relatedness regardless of their education level.

The results based on skill levels (Panel B of Table 7) provide similar insights – high-skilled workers see somewhat smaller negative consequences of robotization when it comes to autonomy, but workers' skills do not attenuate the effect of robots on work meaningfulness, competence, and relatedness.

Finally, Panels C and D of Table 7 detail the results of our heterogeneity analysis based on age group and gender, respectively. Age does not significantly affect the relationship between robots and work meaningfulness and self-determination. More specifically, robotization increases the competence perception of men, likely because robotization rises the productivity of men (Aksoy et al., 2021). Men may perceive their competencies more highly than women because they have more exposure or access to robots, or because they have more confidence or self-efficacy in using them. Alternatively, women may perceive their competencies less strongly than men because they face more barriers or challenges in using robots or because they have more negative or fearful attitudes towards them. Understanding these gender differences may help to design more inclusive and equitable policies and practices for robotization. These patterns should be explored in future research.

Gender, however, does not moderate robots' impact on work meaningfulness, autonomy, and relatedness. Furthermore, the finding that robotization equally erodes the work meaningfulness and self-determination of workers of all ages is interesting, suggesting that employers need to pay attention to workers of all ages and help them adapt to new technologies.

8. Potential mechanisms and alternative explanations

We acknowledge that our ability to definitively pinpoint the mechanisms behind our findings is limited, not least because our dataset comprises pooled cross-sections rather than a panel of individual workers. Nevertheless, we explore several aspects of the data, which provide more detail and help explore the channels.

One possibility is that our results merely reflect job loss and restructuring more generally rather than automation per se. We unfortunately lack information on workers' job spells and previous unemployment experiences. Nevertheless, we have data on workers' job security fears, elicited using the survey item, "I might lose my job in the next 6 months." This allows us to understand whether what we are capturing is fear of the labor-saving aspects of robotization or whether we are measuring the actual job quality consequences of automation. We recoded the original responses, which ranged from strongly agree to strongly disagree on a 5-point scale into 1 = "Agree" and 0 = "Neutral and disagree." The results, reported in Table A6, suggest that individuals experiencing job insecurity are more likely to view their jobs as being less meaningful and bringing less autonomy, and relatedness. Nevertheless, robotization does *not* seem to be amplifying these effects. Therefore, it is unlikely that our results are due to job insecurity and fear of job loss.

Nevertheless, it may still be possible that our results are driven by structural changes affecting different occupations and industries. In Table A4, we demonstrated that the results survive the inclusion of offshorability control and country and year fixed effects. However, it is possible that other structural changes simultaneously coincide with robot adoption. To check whether this is the case, we conduct analyses adding occupation×year interactions and also education×year, which capture shocks that affect whole occupations in particular years, such as, for example, the COVID-19 pandemic, which had differential impacts on workers in different occupations and skills levels. Furthermore, a study by Dixon et al. (2021) finds that robotization leads to a decline in the employment of managers and supervisors employed in a firm, because robots reduce the quality variance, leading to less need for managerial control. If such trends are indeed occupation- or education-level-specific, we could capture them, at least in part, through the use of occupation-by-year or education-by-year fixed effects. The results, reported in Table A7, show that such trends do not seem to influence our results.

Furthermore, we explore whether the effects we document differ across the survey waves, which could shed light on issues related to the temporal distribution of the impacts (Table A8). Importantly, the results seem to be largely consistent across the different survey waves, except autonomy. Specifically, workers in the 2021 EWCS survey seem to have experienced positive and not negative effects of automation as related to autonomy, likely because they have adapted to the previous automation shocks and have learned to benefit from the technology. Alternatively, this finding may be driven by the fact that the 2021 EWCS survey over-sampled highly educated individuals who benefited from more autonomy during the COVID-19 pandemic (Table A9). Whether future technological developments will change these trends or yield similar results and how they will interact with other developments related to the world of work is still an open question that future research should address.

Overall, the findings presented so far suggest that the effects we document do not simply reflect structural changes in the economy and fear of imminent job loss, but rather the consequences of technological change related to robotization. Taken together with the evidence in Section 6, our findings imply that workers performing routine tasks, who are also most affected by industrial robots, are the losers of this process. In contrast, workers who can benefit from the new technologies and have the right skills and occupational background may cushion the negative effects of technology and benefit from it.

9. Discussion and conclusion

This paper studies the implications of robotization for workers' work meaningfulness, autonomy, competence, and relatedness. Our analysis relies on worker-level data from the 2010, 2015, and 2021 European Working Conditions Surveys and data on robotization for 14 industries in 20 countries and OLS and 2SLS estimations. We discover that robotization negatively affects work meaningfulness and autonomy. The results related to competence and relatedness are also negative but less robust. The effect sizes we document imply that doubling robotization reduces work meaningfulness by 0.9 % and autonomy by 1 %.

To provide context for our findings, we compared the robotization levels of the food and beverages industry (the top five industries in terms of robot adoption) and the automotive industry (the leading industry in robot adoption). If the food and beverages industry were to match the level of robot adoption seen in the automotive industry, representing a

7.5-fold increase in robotization, our estimates would imply a decrease of 6.8 % in the meaningfulness of work and a 7.5 % decrease in autonomy, which is economically important.

Future robotization and technology adoption patterns are uncertain. Some industries, such as agriculture or textiles, have relatively low levels of industrial robot penetration that may increase in the future (see Table A1 and Fig. 1). Large increases in the stock of robots per worker are not uncommon across the industries we study, as illustrated in Table A1 and Fig. 1. Industries with low levels of robotization might see large increases in the future because robots are resource and energy-efficient and becoming increasingly enhanced with AI capabilities (IFR, 2023). This is in line with the large increases in robotization seen in the past—a fourfold increase in industrial robots in the US and Western Europe between 1993 and 2007—and what experts predict for the future – a twofold to a fourfold in the next decade (Acemoglu and Restrepo, 2020).

While past automation waves have affected individuals performing routine tasks, future technologies – such as AI – will affect high-skilled workers (Brynjolfsson et al., 2018; Webb, 2020). While all occupations have *some* tasks that can be replaced by machine learning, there are few (if any) occupations in which *all* tasks are replaceable by machine learning (Brynjolfsson et al., 2018). This suggests that the nature of many people's jobs will change in the near future, which has implications for job quality and perceived well-being at work.

Whether our results hold for future automation waves and technological advances remains to be seen. Yet, they provide a useful benchmark against which we could conceptualize the consequences of these currently emerging and future technologies. If technologies are adopted in a democratic and deliberative way, together with all stakeholders including workers, their consequences for future job quality need not be bleak or deterministic. Firms, supported by representative institutions, such as works councils, trade unions, and work committees, can help deliberate strategies for modifying and creating job designs and tasks for workers. Such job designs can ensure that humans and machines cooperate rather than compete for tasks and that the machines help improve workers' well-being.

Against this backdrop, it is important to move beyond the explorations of wage and employment consequences of technology and study the implications for workers' job characteristics and well-being. An emerging body of literature has focused on these understudied aspects, producing mixed results. These emerging studies suggest that adopting industrial robots can hurt workers' job satisfaction and mental health by inducing greater fear of future machine replacement and promoting job insecurity (e.g., Schwabe and Castellacci, 2020; Abeliansky and Beulmann, 2021). The fear and anxiety of future job losses associated with the introduction of smart machines can be particularly pronounced for low-skilled workers who are more likely to perform repetitive tasks.

Our paper provides novel and complementary evidence that robotization erodes workers' well-being regarding work meaningfulness and self-determination related to autonomy and relatedness. Studying the causes and consequences of automation for work meaningfulness and self-determination is instrumental in designing policies to enhance well-being at work. Understanding how automation shapes meaningful work perceptions is key to ensuring worker productivity and health and minimizing turnover amidst the ongoing processes of globalization and automation that can fundamentally change the nature of work.

We acknowledge several limitations to our study that future data collection efforts and extensions can help address. Our paper only focuses on European countries and the subset of industries common in the IFR, EUKLEMS, and EWCS. In this sense, it is unclear whether our findings can be extrapolated to developing countries or countries outside our sample, limiting our geographic generalizability. Moreover, our study faces temporal limitations as our analysis stops in 2021. Furthermore, we lack data on service robots. Our information on industrial robots is likewise imperfect, and we lack details on the characteristics of the robots, including their quality. We also do not have matching industry- or occupation-level information on Artificial Intelligence, the more contemporary form of automation. Despite these challenges, the findings of our paper provide important insights that can be used as the basis for public policy and job design or understanding future technological innovations.

In this sense, our results open up several fruitful avenues for future research. For example, combining employer and employee-level data can help shed light on how firm-level technology adoption and management practices influence workers' work meaningfulness and self-determination outcomes. Our data only provide information on robot exposure at the industry level, but we do not know whether workers in the survey work with robots. Such information can be indispensable to better comprehend the underlying mechanisms behind our findings and provide analyses for particular industries and occupations for which our data are underpowered.

In addition, understanding the technology adoption process and whether or not it is being done in consultation with workers can help shed light on the mechanisms through which workers adapt to new technologies in the workplace. "Democratizing" technology adoption and involving workers in the design and implementation of the process could enhance workers' sense of agency and well-being (Spencer, 2023). Therefore, understanding the role of employee representation structures, such as works councils, trade unions, or other representative committees (Belloc et al., 2022), in technology adoption could be crucial to understanding how robotization can be implemented to satisfy workers' key psychological needs.

Finally, labor market institutions, working arrangements, and the institutional environment significantly differ across countries. While we have accounted for these differences using country-fixed effects, an interesting avenue for future research would be to unpack how the new technologies affect workers' work meaningfulness and self-determination in light of employment protection, technology regulations, and regimes, or institutional characteristics, such as the varieties of capitalism (Hall and Soskice, 2001), which have implications for the organization of labor and inequality.

CRediT authorship contribution statement

Milena Nikolova: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing. **Femke Cnossen:** Data curation, Methodology, Visualization, Writing – review & editing, Conceptualization, Formal analysis. **Boris Nikolaev:** Conceptualization, Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly and ChatGPT to edit and improve the clarity of parts of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This paper has been revised from its initial versions, accessible as GLO Discussion Paper No. 1191 and IZA Discussion Paper No. 16656. The authors thank the Editor Maria Savona, three anonymous referees, Thomas Åstebro, Ylenia Curci, Stefan Jestl, Anthony Lepinteur, Piotr Lewandowski, Marcel Smolka, David Waldenström, as well as seminar participants at Bruegel, the Institute for Industrial Policy (IFN), IOS, and conference participants at the 2023 GI-NI Scientific Conference, the 2022 Society for Quality of Life Studies annual conference, the 2022 European Society for Population Economics (ESPE) conference for helpful comments and suggestions. We thank Viliana Milanova and Stefan Sliwa for providing research assistance. We thank Cevat Aksoy and Julia Philipp for answering all our questions regarding their replication files. This work received support from the Institute for Humane Studies under grant number IHS017216, which allowed the purchase of the 2022 edition of the International Federation of Robotics (IFR) data. All errors are the authors'.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2024.104987.

References

Abeliansky, A., Beulmann, M., 2021. Are they coming for us? Industrial robots and the mental health of workers. Industrial robots and the mental health of workers. cege Discussion Papers, No. 379. Retrieved from: http://hdl.handle.net/10419/201804.

Acemoglu, D., Autor, D.H., Orley, 2011. Chapter 12 - skills, tasks and technologies: Implications for employment and earnings*. In: Ashenfelter, D.C. (Ed.), Handbook of Labor Economics, vol. 4, Part B. Elsevier, pp. 1043–1171.

Acemoglu, D., Restrepo, P., 2019. Automation and new tasks: how technology displaces and reinstates labor. J. Econ. Perspect. 33 (2), 3–30. https://doi.org/10.1257/jep.33.2.3.

Acemoglu, D., Restrepo, P., 2020. Robots and jobs: Evidence from US labor markets. J. Polit. Econ. 128 (6), 2188–2244. https://doi.org/10.1086/705716.

Acemoglu, D., Lelarge, C., Restrepo, P., 2020. Competing with robots: firm-level evidence from France. AEA Papers Proc. 110, 383–388. https://doi.org/10.1257/pandp.20201003.

Acemoglu, D., Koster, H.R., Ozgen, C., 2023. Robots and workers: evidence from the Netherlands. NBER working paper 31009. Retrieved from: https://www.nber.org/papers/w31009.

Adachi, D., Kawaguchi, D., Saito, Y., 2022. Robots and employment: evidence from Japan, 1978-2017. J. Labor Econ. https://doi.org/10.1086/723205.

Aghion, P., Antonin, C., Bunel, S., Jaravel, X., 2020. What are the labor and product market effects of automation? New evidence from France. CEPR discussion paper no. DP14443, available at SSRN. https://ssrn.com/abstract=3547376.

Aksoy, C.G., Özcan, B., Philipp, J., 2021. Robots and the gender pay gap in Europe. Eur. Econ. Rev. 134, 103693.

Anelli, M., Colantone, I., Stanig, P., 2021. Individual vulnerability to industrial robot adoption increases support for the radical right. Proc. Natl. Acad. Sci. 118 (47), e2111611118 https://doi.org/10.1073/pnas.2111611118.

Antón, J.-I., Fernández-Macías, E., Winter-Ebmer, R., 2023. Does robotization affect job quality? Evidence from European regional labor markets. Ind. Relat. J. Econ. Soc. 62 (3), 233–256. https://doi.org/10.1111/irel.12324.

Anzoategui, D., Comin, D., Gertler, M., Martinez, J., 2019. Endogenous technology adoption and R&D as sources of business cycle persistence. Am. Econ. J. Macroecon. 11 (3), 67–110. https://doi.org/10.1257/mac.20170269.

Ariely, D., Kamenica, E., Prelec, D., 2008. Man's search for meaning: the case of Legos. J. Econ. Behav. Organ. 67 (3–4), 671–677. https://doi.org/10.1016/j.jebo.2008.01.004.

Arntz, M., Gregory, T., Zierahn, U., 2016. The risk of automation for jobs in OECD countries: a comparative analysis. In: OECD Social, Employment and Migration Working Papers No. 189, OECD Publishing, Paris. https://doi.org/10.1787/5jlz9h56dvq7-en.

Arntz, M., Gregory, T., Zierahn, U., 2017. Revisiting the risk of automation. Econ. Lett. 159, 157–160. https://doi.org/10.1016/j.econlet.2017.07.001.

Arntz, M., Gregory, T., Zierahn, U., 2019. Digitization and the future of work: macroeconomic consequences. In: Zimmermann, K.F. (Ed.), Handbook of Labor, Human Resources and Population Economics. Springer, pp. 1–29. https://doi.org/10.1007/978-3-319-57365-6_11-1.

Autor, D.H., 2013. The 'task approach' to labor markets: an overview. J. Labour Market Res. 46, 185–199. https://doi.org/10.1007/s12651-013-0128-z.

Autor, D.H., Dorn, D., 2013. The growth of low-skill service jobs and the polarization of the US labor market. Am. Econ. Rev. 103, 1553–1597. https://doi.org/10.1257/aer.103.5.1553.

Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118 (4), 1279–1333. https://doi.org/10.1162/003355303322552801.

Bailey, C., Yeoman, R., Madden, A., Thompson, M., Kerridge, G., 2019. A review of the empirical literature on meaningful work: progress and research agenda. Hum. Resour. Dev. Rev. 18 (1), 83–113. https://doi.org/10.1177/1534484318804653.

Barrett, M., Oborn, E., Orlikowski, W.J., Yates, J., 2012. Reconfiguring boundary relations: robotic innovations in pharmacy work. Organ. Sci. 23 (5), 1448–1466. https://doi.org/10.1287/orsc.1100.0639.

Battisti, M., Gravina, A.F., 2021. Do robots complement or substitute for older workers? Econ. Lett. 208, 110064 https://doi.org/10.1016/j.econlet.2021.110064.

Baumgarten, D., Geishecker, I., Görg, H., 2013. Offshoring, tasks, and the skill-wage pattern. Eur. Econ. Rev. 61, 132–152. https://doi.org/10.1016/j.euroecorev.2013.03.007.

Bekhtiar, K., Bittschi, B., Sellner, R., 2021. Robots at work? Pitfalls of industry level data. EconPol Working Paper 58. Retrieved from. https://www.econpol.eu/sites/default/files/2021-02/EconPol_Working_Paper_58_Robots_at_work.pdf.

Bellemare, M.F., Wichman, C.J., 2020. Elasticities and the inverse hyperbolic sine transformation. Oxf. Bull. Econ. Stat. 82 (1), 50–61. https://doi.org/10.1111/obes.12325.

Belloc, F., Burdin, G., Cattani, L., Ellis, W., Landini, F., 2022. Coevolution of job automation risk and workplace governance. Res. Policy 51 (3), 104441. https://doi.org/10.1016/j.respol.2021.104441.

Berg, J., 2019. Protecting workers in the digital age: technology, outsourcing, and the growing precariousness of work. Comp. Labor Law Policy J. 41, 69. Retrieved from. https://heinonline.org/HOL/LandingPage?handle=hein.journals/cllpj41&div=7&id=&page=.

Berg, J., Green, F., Nurski, L., Spencer, D.A., 2023. Risks to job quality from digital technologies: are industrial relations in Europe ready for the challenge? Eur. J. Ind. Relat. 09596801231178904.

Bessen, J., Goos, M., Salomons, A., van den Berge, W., 2020. Firm-level automation: evidence from the Netherlands. AEA Pap. Proc. 110, 389–393. https://doi.org/10.1257/pandp.20201004.

Bonin, H., Gregory, T., Zierahn, U., 2015. Übertragung der Studie von Frey/Osborne (2013) auf Deutschland. Retrieved from. https://ftp.zew.de/pub/zew-docs/gutachten/Kurzexpertise_BMAS_ZEW2015.pdf.

Borjas, G.J., Freeman, R.B., 2019. From immigrants to robots: the changing locus of substitutes for workers. *RSF: the Russell Sage Foundation.* J. Soc. Sci. 5 (5), 22–42. https://doi.org/10.7758/RSF.2019.5.5.02.

Bowles, J., 2014, July 24. The computerisation of European jobs. In: Bruegel | The Brussels-based Economic Think Tank. https://www.bruegel.org/blog-post/computerisation-european-jobs.

Brynjolfsson, E., Mitchell, T., Rock, D., 2018. What Can Machines Learn, and What Does it Mean for Occupations and the Economy? Paper Presented at the AEA Papers and Proceedings.

Cassar, L., Meier, S., 2018. Nonmonetary incentives and the implications of work as a source of meaning. J. Econ. Perspect. 32 (3), 215–238. https://doi.org/10.1257/jep.32.3.215.

Castellacci, F., Tveito, V., 2018. Internet use and well-being: a survey and a theoretical framework. Res. Policy 47 (1), 308–325. https://doi.org/10.1016/j.respol.2017.11.007.

Clark, A.E., 2015. What makes a good job? Job quality and job satisfaction. IZA World Labor 215. https://doi.org/10.15185/izawol.215.

Colbert, A.E., Bono, J.E., Purvanova, R.K., 2016. Flourishing via workplace relationships: moving beyond instrumental support. Acad. Manage. J. 59 (4), 1199–1223. https://doi.org/10.5465/amj.2014.0506.

Couch, K.A., Placzek, D.W., 2010. Earnings losses of displaced workers revisited. Am. Econ. Rev. 100 (1), 572–589. https://doi.org/10.1257/aer.100.1.572.

Dauth, W., Findeisen, S., Suedekum, J., Woessner, N., 2021. The adjustment of labor markets to robots. J. Eur. Econ. Assoc. https://doi.org/10.1093/jeea/jvab012.

De Vries, G.J., Gentile, E., Miroudot, S., Wacker, K.M., 2020. The rise of robots and the fall of routine jobs. Labour Econ. 66, 101885 https://doi.org/10.1016/j.labeco.2020.101885.

De Witte, H., Pienaar, J., De Cuyper, N., 2016. Review of 30 years of longitudinal studies on the association between job insecurity and health and well-being: is there causal evidence? Aust. Psychol. 51 (1), 18–31.

Deci, E., Ryan, R.M., 1985. Intrinsic Motivation and Self-Determination in Human Behavior. Plenum Press, New York.

Deci, E.L., Ryan, R.M., 2000. The "what" and "why" of goal pursuits: human needs and the self-determination of behavior. Psychol. Inq. 11 (4), 227–268.

Dekker, F., Salomons, A., Waal, J., v. d., 2017. Fear of robots at work: the role of economic self-interest. Soc. Econ. Rev. 15 (3), 539–562.

Dixon, J., Hong, B., Wu, L., 2021. The robot revolution: managerial and employment consequences for firms. Manag. Sci. 67 (9), 5586–5605. https://doi.org/10.1287/mnsc.2020.3812.

Eurofound, 2022. European Working Conditions Survey, 2010. [data collection]. UK Data Service. SN: 6971. https://doi.org/10.5255/UKDA-SN-6971-2.

Eurofound, 2023a. European Working Conditions Survey, 2015. [data collection]. 4th Edition. UK Data Service. SN: 8098. https://doi.org/10.5255/UKDA-SN-8098-5.

Eurofound, 2023b. European Working Conditions Telephone Survey, 2021. [data collection]. 2nd Edition. UK Data Service. SN: 9026. https://doi.org/10.5255/UKDA-SN-9026-2.

European Commission, 2021. European Citizens' Knowledge and Attitudes Towards Science and Technology. Special Eurobarometer 516. Report. https://doi.org/10.2775/071577.

Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? Technol. Forecast. Soc. Chang. 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019.

Gihleb, R., Giuntella, O., Stella, L., Wang, T., 2022. Industrial robots, workers' safety, and health. Labour Econ. 78, 102205 https://doi.org/10.1016/j.labeco.2022.102205.

Giuntella, O., Lu, Y., Wang, T., 2022. How do workers and households adjust to robots? Evidence from China. National Bureau of Economic Research Working Paper Series 30707. https://doi.org/10.3386/w30707.

Gombolay, M.C., Gutierrez, R.A., Clarke, S.G., Sturla, G.F., Shah, J.A., 2015. Decision-making authority, team efficiency and human worker satisfaction in mixed human–robot teams. Auton Robots 39 (3), 293–312. https://doi.org/10.1007/s10514-015-9457-9.

Gorny, P.M., Woodard, R.C., 2020. Don't Fear the Robots: Automatability and Job Satisfaction. MPRA Paper 103424. University Library of Munich, Germany. Retrieved from Link. https://mpra.ub.uni-muenchen.de/103424/.

Graetz, G., Michaels, G., 2018. Robots at work. Rev. Econ. Stat. 100 (5), 753–768. https://doi.org/10.1162/rest_a_00754.

Green, F., 2006. Demanding Work: The Paradox of Job Quality in the Affluent Economy. Princeton University Press, Princeton, NJ, USA.

Gregory, T., Salomons, A., Zierahn, U., 2021. Racing with or against the machine? Evidence on the role of trade in Europe. J. Eur. Econ. Assoc. 20 (2), 869–906. https://doi.org/10.1093/jeea/jvab040.

Gunadi, C., Ryu, H., 2021. Does the rise of robotic technology make people healthier? Health Econ. 30 (9), 2047–2062. https://doi.org/10.1002/hec.4361.

Hackman, R.J., Oldham, G., 1976. Motivation through the design of work: test of a theory. Organ. Behav. Hum. Perform. 16 (2), 250–279. https://doi.org/10.1016/0030-5073(76)90016-7.

Hall, P.A., Soskice, D., 2001. Varieties of Capitalism: The Institutional Foundations of Comparative Advantage. Oxford University Press.

Hinks, T., 2021. Fear of robots and life satisfaction. Int. J. Soc. Robot. 13, 327–340.

Hu, J., Hirsh, J.B., 2017. Accepting lower salaries for meaningful work. Front. Psychol. 8, 1–10. https://doi.org/10.3389/fpsyg.2017.01649, 1649.

Huckfeldt, C., 2022. Understanding the scarring effect of recessions. Am. Econ. Rev. 112 (4), 1273–1310. https://doi.org/10.1257/aer.20160449.

IFR. (International Federation of Robotics), 2023. Top 5 Robot Trends 2023. IFR International Federation of Robotics. https://ifr.org/ifr-press-releases/news/top-5-robot-trends-2023.

IFR. International Federation of Robotics, 2021. Introduction. Retrieved from. https://ifr.org/img/worldrobotics/WR_Industrial_Robots_2021_Chapter_1.pdf.

Ipsos, N.V., 2022. Working conditions and sustainable work: European working conditions telephone survey 2021: technical report. Reference WPEF22050. Link. https://www.eurofound.europa.eu/sites/default/files/wpef22050.pdf.

Jestl, S. Industrial robots, and information and communication technology: the employment effects in EU labour markets. Regional Studies, 1–18. doi:https://doi.org/10.1080/00343404.2023.2292259.

Jurkat, A., Klump, R., Schneider, F., 2022. Tracking the rise of robots: the IFR database. Jahrbücher für Nationalökonomie und Statistik. https://doi.org/10.1515/jbnst-2021-0059.

Kassenboehmer, S.C., Haisken-DeNew, J.P., 2009. You're fired! The causal negative effect of entry unemployment on life satisfaction. Econ. J. 119 (536), 448–462. https://doi.org/10.1111/j.1468-0297.2008.02246.x.

Kesternich, I., Schumacher, H., Siflinger, B., Schwarz, S., 2021. Money or meaning? Labor supply responses to work meaning of employed and unemployed individuals. Eur. Econ. Rev. 137, 103786 https://doi.org/10.1016/j.euroecorev.2021.103786.

Koch, M., Manuylov, I., Smolka, M., 2021. Robots and firms. Econ. J. 131 (638), 2553–2584. https://doi.org/10.1093/ej/ueab009.

Leduc, S., Liu, Z., 2023. Automation, bargaining power, and labor market fluctuations. In: Federal Reserve Bank of San Francisco Working Paper 2019-17. https://doi.org/10.24148/wp2019-17. Available at.

Lordan, G., Stringer, E.-J., 2022. People versus machines: the impact of being in an automatable job on Australian worker's mental health and life satisfaction. Econ. Human Biol. 46, 101144 https://doi.org/10.1016/j.ehb.2022.101144.

Marr, B., 2017. The 4 Ds of Robotization: Dull, Dirty, Dangerous and Dear. Forbes. Retrieved from. https://www.forbes.com/sites/bernardmarr/2017/10/16/the-4-ds-of-robotization-dull-dirty-dangerous-and-dear/?sh=190223013e0d.

Martin, L., Hauret, L., 2022. Digitalization, job quality, and subjective well-being. In: Zimmermann, K.F. (Ed.), Handbook of Labor, Human Resources and Population Economics. Springer International Publishing, Cham, pp. 1–41. https://doi.org/10.1007/978-3-319-57365-6_388-1.

Mokyr, J., Vickers, C., Ziebarth, N.L., 2015. The history of technological anxiety and the future of economic growth: is this time different? J. Econ. Perspect. 29 (3), 31–50. https://doi.org/10.1257/jep.29.3.31.

Nedelkoska, L., Quintini, G., 2018. Automation, Skills Use and Training. Retrieved from OECD Paris, France. https://www.sipotra.it/wp-content/uploads/2018/05/Automation-skills-use-and-training.pdf.

Nikolova, M., Ayhan, S.H., 2019. Your spouse is fired! How much do you care? J. Popul. Econ. 32 (3), 799–844. https://doi.org/10.1007/s11187-020-00374-4.

Nikolova, M., Cnossen, F., 2020. What makes work meaningful and why economists should care about it. Labour Econ. 65, 101847 https://doi.org/10.1016/j.labeco.2020.101847.

Nikolova, M., Nikolaev, B., Popova, O., 2021. The perceived well-being and health costs of exiting self-employment. Small Bus. Econ. 57 (4), 1819–1836. https://doi.org/10.1007/s11187-020-00374-4.

Nikolova, M., Nikolaev, B., Boudreaux, C., 2022. Being your boss and bossing others: the moderating effect of managing others on work meaning and autonomy for the self-employed and employees. Small Bus. Econ. https://doi.org/10.1007/s11187-021-00597-z.

O'Brien, R., Bair, E.F., Venkataramani, A.S., 2022. Death by robots? Automation and working-age mortality in the United States. Demography 59 (2), 607–628. https://doi.org/10.1111/apps.12241.

Pajarinen, M., Rouvinen, P., 2014. Computerization threatens one third of Finnish employment. Etla Brief 22 (13.1), 2014. Retrieved from: https://www.etla.fi/wp-content/uploads/ETLA-Muistio-Brief-22.pdf.

Parker, S.K., Grote, G., 2020. Automation, algorithms, and beyond: why work design matters more than ever in a digital world. Appl. Psychol. https://doi.org/10.1111/apps.12241.

Patel, P.C., Devaraj, S., Hicks, M.J., Wornell, E.J., 2018. County-level job automation risk and health: evidence from the United States. Soc. Sci. Med. 202, 54–60.

Reichert, A.R., Tauchmann, H., 2017. Workforce reduction, subjective job insecurity, and mental health. J. Econ. Behav. Org. 133, 187–212. https://doi.org/10.1016/j.jebo.2016.10.018.

Rosso, B.D., Dekas, K.H., Wrzesniewski, A., 2010. On the meaning of work: a theoretical integration and review. Res. Organ. Behav. 30, 91–127. https://doi.org/10.1016/j.riob.2010.09.001.

Ryan, R.M., Deci, E.L., 2001. On happiness and human potentials: a review of research on hedonic and eudaimonic well-being. Annu. Rev. Psychol. 52 (1), 141–166. https://doi.org/10.1521/978.14625/28806.

Ryan, R.M., Deci, E.L., 2017. Self-determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness. Guilford Publications. https://doi.org/10.1521/978.14625/28806.

Sachs, J.D., Kotlikoff, L.J., 2012. Smart machines and long-term misery. Retrieved from. https://www.nber.org/system/files/working_papers/w18629/w18629.pdf.

Schwabe, H., Castellacci, F., 2020. Automation, workers' skills and job satisfaction. PloS One 15 (11), e0242929. https://doi.org/10.1371/journal.pone.0242929.

Simonsohn, U., Simmons, J.P., Nelson, L.D., 2020. Specification curve analysis. Nat. Hum. Behav. 4 (11), 1208–1214. https://doi.org/10.1038/s41562-020-0912-z.

Smids, J., Nyholm, S., Berkers, H., 2020. Robots in the workplace: a threat to—or opportunity for—meaningful work? Phil. Technol. 33 (3), 503–522. https://doi.org/10.1007/s13347-019-00377-4.

Spencer, D.A., 2018. Fear and hope in an age of mass automation: debating the future of work. N. Technol. Work. Employ. 33 (1), 1–12. https://doi.org/10.1111/ntwe.12105.

Spencer, D.A., 2023. Technology and work: past lessons and future directions. Technol. Soc. 102294 https://doi.org/10.1016/j.techsoc.2023.102294.

Spitz-Oener, A., 2006. Technical change, job tasks, and rising educational demands: looking outside the wage structure. J. Labor Econ. 24 (2), 235–270. https://doi.org/10.1086/499972.

Webb, M., 2020. The Impact of Artificial Intelligence on the Labor Market. Available at SSRN. https://doi.org/10.2139/ssrn.3482150.