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ABSTRACT

The dynamic processes of automation and digitalisation rapidly transform the labour market. Better adaptation to these processes at the individual level relies on knowledge and perceptions of the situation, as reflected by attitudes in large-scale data. This paper combines the theory of the digital divide, which focuses on inequalities, with the ecological perspective providing a framework for studying how attitudes towards digitalisation are connected to several micro-, meso-, and macro-factors. The topic is addressed with data from the Eurobarometer via multilevel regression analysis of respondents nested in contexts, focusing on the attitudes of older workers towards the impact of digitalisation and their differences indicating the digital divide. Generally, digitalisation of work is perceived rather positively, with large differences between groups of individuals. New technologies are consistently perceived more negatively by workers that are older, have lower skills, work in manual jobs, live in a village, and do not support the EU, whilst other characteristics show more complex relationships. Moreover, attitudes towards the digitalisation of work are more negative in contexts characterised by higher unemployment, lower prevalence of training for older workers, and a lower level of digitalisation. The paper discusses the need to identify groups of older workers with a more negative approach to technologies and develop appropriate policies to reduce the digital divide and the potential exclusion of these groups from the labour market.

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Introduction

Industry 4.0 represents a significant change in workforce competencies. In addition to traditional competencies such as communication, creativity, and willingness to learn, Industry 4.0 brings new skills in areas such as digital networks and digital security. Integral to Industry 4.0 are concepts such as automation, digitalisation and robotisation (Hecklau et al., 2017). These processes represent radical changes to the labour market. These changes can be seen from many angles, as they affect various groups of workers

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differently, based on age, gender, qualification, and type of job differently (Domini et al., 2022; Snell & Gekara, 2023). Moreover, automation, robotisation, and digitalisation are not adequately discussed with employees, who might fear that their work will become more difficult or that their jobs will be eliminated (Marinoudi et al., 2021).

The inception of Industry 4.0 currently overlaps with another vast social challenge of population ageing. European societies face an increase in the proportion of senior citizens, a rising pension age, and a growing proportion of working older adults (Maltby et al., 2017). Moreover, Eurofound (2012) shows that some retirees seek part-time work after retirement. New technologies can be more challenging for older workers compared to younger workers, because of their generally lower experience with digital tools, lower digital skills, age stereotypes, and age discrimination (McCann & Keaton, 2013). According to Vasilescu et al. (2020), older workers with lower digital skills and relatively low income are the most vulnerable to digitalisation. Hence, the empirical part of this study focuses on workers aged 50+ and their attitudes towards digitalisation in the labour market. This focus aims to understand their attitudes and these vary, in order to identify potentially threatened groups of older workers and make their transition to the digital economy as smooth as possible.

Although some previous studies used the Eurobarometer survey data for similar purposes (Carradore, 2022; Turja & Oksanen, 2019; Vasilescu et al., 2020), their empirical scope was limited. Furthermore, other studies cited in this text focused on a limited spectrum of both predictors and indicators of attitudes. Hence, this research expands the existing knowledge by combining the ecological perspective with the digital divide via the development of its multilevel nature and addresses the research question *Which factors at three analytical levels shape attitudes towards digitalisation in the European context?* In doing so, the study examines the role of a variety of individual characteristics, household and community characteristics, and several contextual aspects in shaping multiple types of attitudes towards technologies. Furthermore, the central expectation that groups of older workers left behind by digitalisation can form more negative attitudes towards technologies and be less adaptive in the labour market is tested. The next sections elaborate on the theoretical grounding of this study, summarise the existing findings on factors affecting attitudes in this area, and outline the empirical contribution described in this paragraph.

Theoretical groundings

Digitalisation does not reduce the demand for low-skilled jobs that do not require higher education (Schaupp, 2022). Lawrence et al. (2017) argue that automation does not lead to the elimination of work but rather facilitates its transformation. However, other studies conclude that the acceleration of automation may slow labour demand in manufacturing (Acemoglu & Restrepo, 2019) and various other types of jobs based on more routine tasks (Frey & Osborne, 2017).

The implications of digitalisation processes impact different groups of workers differently, and this actual impact may not align with their actual expectations. Certain conditions shape the perception of technology, and this perception – according to the technology acceptance model (Schepers & Wetzels, 2007) – affects its actual usage. However, this study argues that the situation of older workers is much more complex, as their options include technology rejection, technology acceptance, career changes such as requalification, and early retirement. It draws on the theory of the digital divide in order to anticipate and test the differences in attitudes towards digitalisation amongst older workers.

The theory of the digital divide was developed by Van Dijk (2006) and illustrates technological inequalities in access, skills, and usage (Helsper, 2021). Whilst different conceptions of the digital divide show different levels of technological inequalities, these inequalities will exist as long as individual differences persist (Helsper, 2021). The notion of the divide is mainly associated with rural-urban differences in access to communication infrastructure, income, age, education, and similar factors (Vasilescu et al., 2020). Nevertheless, the digital divide can also be located amongst groups differing in economic, social, and cultural capital, as well as amongst countries or broader geographical regions (Helsper, 2021).

The ecological perspective, alongside other theoretical approaches, states that social processes occur within a complex system of relationships and environments (Bronfenbrenner, 1977, 1986). This complex system of a multi-layered nature (with micro-, meso-, and macrosystem, amongst others) was originally used to study its impacts on children's growth and well-being, but it applies to other topics as well (Bronfenbrenner, 1977). Therefore, this study uses the ecological perspective as a framework for understanding the multi-layered social reality shaping the attitudes of older workers towards digitalisation.

Then, the connection between the theory of the digital divide and the ecological perspective in this paper develops the argument that important inequalities in access and skills exist at the micro-, meso-, and macro-level of social reality. Within this combination, the ecological perspective provides an analytical approach that draws attention to several levels of social reality shaping human attitudes and actions, but it does not bring specific expectations about important factors at the three levels. Hence, the ecological perspective is linked to the theory of the digital divide as a basis for forming expectations of inequalities along several lines and levels of social divides. These divides result from different types of inequalities (including technological) and further shape perceptions and behaviour (arguably including attitudes towards digitalisation). This approach appears to be more fitting for explaining how older workers deal with technologies than the above-mentioned technology acceptance model or the contact hypothesis (Allport, 1954). Therefore, the ecological perspective reflects the multi-layered social reality and the theory of the digital divide – combined with the previous findings – leads to expectations of specific empirical associations in the form of hypotheses.

Sociodemographic factors

Age, gender, education, and financial situation seem to be the most profound individual factors related to digitalisation, robotisation, and automation. For example, women and men are equally concerned about the effects of automation (Ivanov et al., 2020). What may be different is that women are generally better at coping with changes in the workplace (generally more adaptable to change) caused by automation, whilst the gender pay gap is not directly affected by automation (Domini et al., 2022; Ivanov et al., 2020). Introducing new technologies can cause technophobia, which is most frequent in men over 49 (Xi et al., 2022). Moreover, older people (55+) are much less digitally skilled (Vasilescu et al., 2020) and more stressed by telework (Klarsfeld et al., 2024). Additionally, people with lower incomes support more employment measures introduced by the government (for example, higher taxation on businesses replacing human employees with automated systems or robots) (Ivanov et al., 2020). This support could signify a search for certainty in policy action amongst lower-income citizens.

H1a: Higher age is associated with less positive attitudes towards digitalisation.

H1b: Being a man is associated with less positive attitudes towards digitalisation.

H1c: A higher level of education is associated with more positive attitudes towards digitalisation.

H1d: A worse financial situation is associated with less positive attitudes towards digitalisation.

Other individual factors

Digital skills, type of job, and opinions related to societal issues are other individual characteristics potentially associated with attitudes towards digitalisation (at work). Digital skills can be closely related to the perception of technologies, which is illustrated by a better perception of so-called social robots by people who have already encountered AI (Carradore, 2022). The anxiety about using technology amongst older workers is not necessarily linked to ageing, gender, or education but, rather, to the ability to operate technology autonomously (Di Giacomo et al., 2020). Given the population ageing and increasing retirement age, the low digital skills of older adults could be a significant problem for the EU. If older workers do not have sufficient digital skills, digitalisation may mean narrowing the choice of possible jobs. The type of job is partly related to digital skills (with some jobs based more on technology usage and higher digital skills) and partly to the thread of automation in a given field. Since the differences in digital skills are controlled for, we could expect that jobs with higher uncertainty/more threatened by automation are associated with worse attitudes towards it (Vasilescu et al., 2020). Finally, other attitudes, opinions, and internalised social norms can be connected to the concept explored. For instance, attitudes representing fear of globalisation and economic transformation (e.g., negative attitudes towards the EU) may lead to a worse perception of digitalisation.

H2a: Higher digital skills are associated with more positive attitudes towards digitalisation.

H2b: Manual jobs are associated with less positive attitudes towards digitalisation.

H2c: Negative attitudes towards EU membership are associated with less positive attitudes towards digitalisation.

Meso-contextual factors

Applying the ecological perspective (Bronfenbrenner, 1977, 1986), this paper adds the level of household, community, country, and time period and their connection to individual attitudes to previous studies (Carradore, 2022; Turja & Oksanen, 2019) on similar topics. This section focuses on the more proximate context (household, community), whilst the next section discusses the findings about the role of countries and larger geographical regions.

Characteristics of household and community (for simplicity, included in the meso level) have not been extensively studied, but the theory of the digital divide brings some assumptions for these contexts, too. It is assumed that households with married individuals and dependent children may – *ceteris paribus* – form more negative attitudes towards digitalisation if perceiving this process as threatening their jobs. So far, the only study associating marital status with fear of digitalisation has not found any relationship in the limited U.S. sample (McClure, 2018); this paper argues that having dependent children is more important for job insecurity than marital status and uses this indicator of family composition. Additionally, workers in rural areas and villages may be confronted with lower availability of technologies and access to the Internet, lower digital skills, and less digitalised job positions (Carradore, 2022). On the other hand, Bell (2007) summarised a long-term discussion about diminishing differences between urban and rural areas in the European context, although some types of differences can prevail.

H3a: Less positive attitudes towards digitalisation are more prevalent in households with children.

H3b: Less positive attitudes towards digitalisation are more prevalent in rural areas.

Macro-contextual factors

At the general level of cross-national differences, Makó and Illéssy (2020) showed that Nordic countries have the highest number of so-called 'creative workers' characterised by a higher degree and usage of cognitive abilities. In contrast, Mediterranean countries have the lowest number of such workers. Creative jobs account for up to three quarters of all jobs in the Nordic countries. These positions are (nowadays) relatively resistant to the introduction of automation in the workplace (Makó & Illéssy, 2020), which may nevertheless change with the development of AI. In contrast to creative jobs, agriculture is dominated by manual and routine work, and thus workers in this sector can be susceptible to further automation (Marinoudi et al., 2021).

Whilst the overall GDP is not associated with attitudes towards digitalisation at work (Carradore, 2022) and cultural dimensions of countries with adaptation of HR analytics (Bechter et al., 2022), the ratio of jobs threatened by automation relates negatively to these attitudes (Turja & Oksanen, 2019). This paper argues that absolute economic performance is not as decisive as (a) labour market opportunities and (b) the structure of the economy; both indicating perceived and actual consequences of digitalisation. For instance, a higher level of unemployment (bringing more uncertainty) may lead to more negative attitudes towards digitalisation even if the actual risk of job automation is not higher. Turja and Oksanen (2019) mention the so-called cultural aspect of robotisation in their research, noting that countries with the highest levels of robotisation in the EU do not show the highest levels of robot acceptance. Specifically, countries categorised as 'traditionally Catholic Mediterranean countries' (e.g., Spain, Italy, etc.) are the most likely to represent a certain conservatism in the prevailing attitudes. However, the effect of cultural aspects may be rather indirect through its impact on workplace practices. For instance, conservative settings may lead to more ageism at the workplace and lower emphasis on the development of new skills (Turja & Oksanen, 2019). Hence, older workers can have fewer opportunities for further training and, in turn, develop more negative attitudes towards technologies. This paper prefers to capture the cultural aspect by the availability of training for older workers – rather than by indicating religion – at the country level and attitudes towards the EU at the individual level.

> H4a: Less positive attitudes towards digitalisation are more prevalent in countries with a higher unemployment rate.

> H4b: Less positive attitudes towards digitalisation are more prevalent in countries with higher availability of training for older workers.

The existing studies of contextual factors shaping robot acceptance examine mainly technical aspects such as the mobile phone ratio and ICT exports. Turja and Oksanen (2019) found these characteristics relevant, whilst Carradore (2022) did not. More importantly, similar indicators are at hand; this study opts for a more general (and multidimensional) measurement of the level of digitalisation in a country known as the DESI index. Moreover, the structure of the economy in terms of economic sectors was not addressed in previous research. The proportion of workers in a service sector may lead to the environment being favourable to robotisation because the risks of automation still prevail in the primary and secondary sectors (Di Giacomo et al., 2020).

> H4c: Less positive attitudes towards digitalisation are more prevalent in countries with a lower level of digitalisation.

> H4d: Less positive attitudes towards digitalisation are more prevalent in countries with a lower share of workers in the service sector.

Data and analysis

Data source

This study uses data from two Eurobarometer surveys conducted by the European Commission in November-December 2014 and March 2017. The data from 2014 come from Eurobarometer 82.4, dedicated to topics of the European Parliament, autonomous systems, gender equality, and smoking habits (European Commission, 2018). The data from 2017 was collected in Eurobarometer 87.1, which inquired about the European elections, tobacco and electronic cigarettes, climate change, digitalisation and automation, and coach services (European Commission, 2021a). Both data sets are cross-sectional and include representative samples of all EU member states interviewed by the Computer Assisted Personal Interview technique. Some parts of the questionnaires for these surveys differ (e.g., other included topics, items of some batteries, coding of some sociodemographic variables), but the core parts are comparable over time. The key part is the questionnaire section called 'Autonomous systems' in 2014 and 'Attitudes towards the impact of digitisation and automation on daily life' in 2017, which includes questions on perceptions, notions and attitudes in the area of digitalisation and autonomous intelligence (in the labour market). These two datasets contain comparable measures of both attitudes and more general socioeconomic characteristics, which make it possible to merge them and obtain a more robust dataset encompassing data from more contexts. Subsequently, the individual-level data from the two Eurobarometer surveys were supplemented by additional data sources of macro-indicators, namely the World Bank database (World Bank, 2022), the European Commission (European Commission, 2021b), and the United Nations (UNECE, 2019).

The data preparation included several steps. Apart from merging the two surveys and supplementing them with four external macro-variables, it also included merging West Germany with East Germany and Great Britain with Northern Ireland. The analysis then uses only older workers, meaning respondents between 50 and 70 years of age working at the time of the interview, which is the most common lower and upper limit for defining this age group according to the review study of Zacher et al. (2019). Those not working were dropped because they did not answer some key questions. Finally, 8,668 respondents (10.5%) were dropped due to missing value(s), which made the final sample of 7,759 respondents. This study also uses four contextual variables in order to examine individual and contextual factors shaping attitudes towards digitalisation of work. The context is defined as a country in a given year (2014/2017), which reflects both socio-geographic variability and change over time in the context of the EU. The resulting data structure comprises 7,759 individuals nested in 56 country*year contexts, with value distributions shown in Table 1.

Dependent variables

The analysis employs three dependent variables capturing diverse attitudes towards digitalisation in the labour market measured in both waves of the Eurobarometer, all measured on an ordinal 4-point scale. This way, it aims to capture different theoretically grounded attitudes (Watson et al., 1988) to provide a more complex depiction of the topic. First, *negative cognition* is identified by asking ‘Do you think your current job could be done by a robot in the future?’ in 2014 and ‘Do you think your current job could be done by a robot or by artificial intelligence in the future?’ in 2017. Adding the concept of artificial intelligence (AI) by survey preparators in 2017 seems quite farsighted. In any case, the options for both data collections were ‘not at all’, ‘partially’, ‘mostly’, and ‘entirely’. Second, respondents could choose from ‘totally disagree’ to ‘totally agree’ for the item ‘Robots steal peoples’ jobs’ (2014) and ‘Robots and artificial intelligence steal peoples’ jobs’ (2014), measuring *negative affect*. Finally, the same scale of agreement measured the *positive affect* towards digitalisation by the item ‘Robots are a good thing for society, because they help people’ (2014) and ‘Robots and artificial intelligence are a good thing for society, because they help people do their jobs or carry out daily tasks at home’ (2017).

Predictors measured at the individual level

Firstly, two individual predictors are used as continuous variables with age (range 50-70) and top/down-coded age at completion of education (range from up to 14–22 and older); the linearity of their coefficients was confirmed. Secondly, two variables are of a binary nature – gender is coded as man = 0 and woman = 1, children in the household as an indicator of dependent family members with values no = 0 and yes = 1. Finally, other characteristics theoretically connected to dependent variables are categorical variables with the lowest value as a reference category in the analysis. These categorical variables are financial difficulties (most of the time = 1, from time to time = 2, never = 3); type of

Table 1. Descriptive statistics of the sample (percentages rounded to one decimal place and means to two decimal places).

Variable	Categories or range	Total (% or mean)	Wave 2014 (% or mean)	Wave 2017 (% or mean)
Current job done by a robot (negative cognition)	Not at all	60.5	65.9	55.5
	Partially	25.4	23.0	27.7
	Mostly	10.4	8.4	12.2
	Entirely	3.7	2.7	4.6
Robots steal jobs (negative affect)	Totally disagree	7.8	9.2	6.6
	Tend to disagree	19.8	19.8	19.9
	Tend to agree	35.9	34.1	37.5
	Totally agree	36.4	36.9	36.0
Robots help people (positive affect)	Totally disagree	6.0	5.8	6.2
	Tend to disagree	16.1	13.9	18.1
	Tend to agree	50.6	49.9	51.2
	Totally agree	27.3	30.4	24.5
Age	50–70	56.48	56.32	56.63
Gender	Man	49.6	50.5	48.7
	Woman	50.4	49.5	51.3
Education	14–22	19.08	18.98	19.17
Children in the household	Yes	37.4	38.1	36.9
Financial difficulties	Most of the time	7.2	7.7	6.8
	From time to time	22.4	22.2	22.5
	Never	70.4	70.1	70.6
Type of job	Manual workers	27.0	27.3	26.7
	Employees in service sector	27.0	26.8	27.2
	Managers and professionals	34.9	35.0	34.8
	Self-employed	11.1	10.9	11.3
Internet usage	Less often or never	17.9	21.5	14.5
	Weekly or monthly	11.4	12.0	10.8
	Daily	70.8	66.5	74.7
Type of community	Rural area or village	30.7	29.2	32.1
	Small/middle town	40.5	42.6	38.5
	Large town/city	28.8	28.2	29.4
EU membership	A bad thing	20.2	28.4	12.7
	Neither good nor bad	21.1	13.9	27.7
	A good thing	58.7	57.7	59.7
Unemployment rate	2.9–26.5	8.57	9.99	7.27
Training of older people	0.1–22.7	5.47	5.30	5.63
Level of digitalisation	34.6–66.9	47.79	43.84	51.43
Workers in service sector	47.1–87.8	70.65	70.46	71.83
N		7,759	3,719	4,040

Notes: These calculations use data from Eurostat 2014 and 2017.

job (manual workers = 1, employees in service sector = 2, managers and professionals = 3, self-employed = 4); digital skills indicated by Internet usage (less often or never = 1, weekly or monthly = 2, daily = 3); type of community (rural area or village = 1, small/middle town = 2, large town/city = 3); and attitudes towards EU membership (a bad thing = 1, neither good nor bad = 2, a good thing = 3). Notably, having children and rurality are conceptualised as meso-level characteristics, but the indicators are only available at the individual level.

Predictors measured at the contextual level

This study tests four continuous macro-factors from three data sources, which could affect attitudes towards digitalisation according to the literature. The values of the unemployment rate in percentages and the percentages of workers in the service sector come from the World Bank database (World Bank, 2022). The percentage of older people who have recently received education or training comes from the Active Ageing Index published by UNECE (UNECE, 2019). The level of digitalisation is indicated by the Digital Economy and Society Index – the DESI index (European Commission, 2021b) constructed by Eurostat since 2014 (DESI has been published in several versions and this paper uses values obtained directly from the data provider). Ranges and means of all scales are provided in Table 1, and their specific values are shown in Figures 1 and 2.

Analytical strategy

The two-level data structure and the ordinal character of the dependent variables have led to the estimation of multilevel ordinal logistic regression with random intercept as the only random effect, using SPSS 22 and its command GENLINMIXED (with LOGIT function). The paper tests nine individual and four contextual predictors, but 56 level-2 observations and the estimation mechanism make it possible to use only two macro-variables in one model, whilst using countries as the level-2 observations would not even

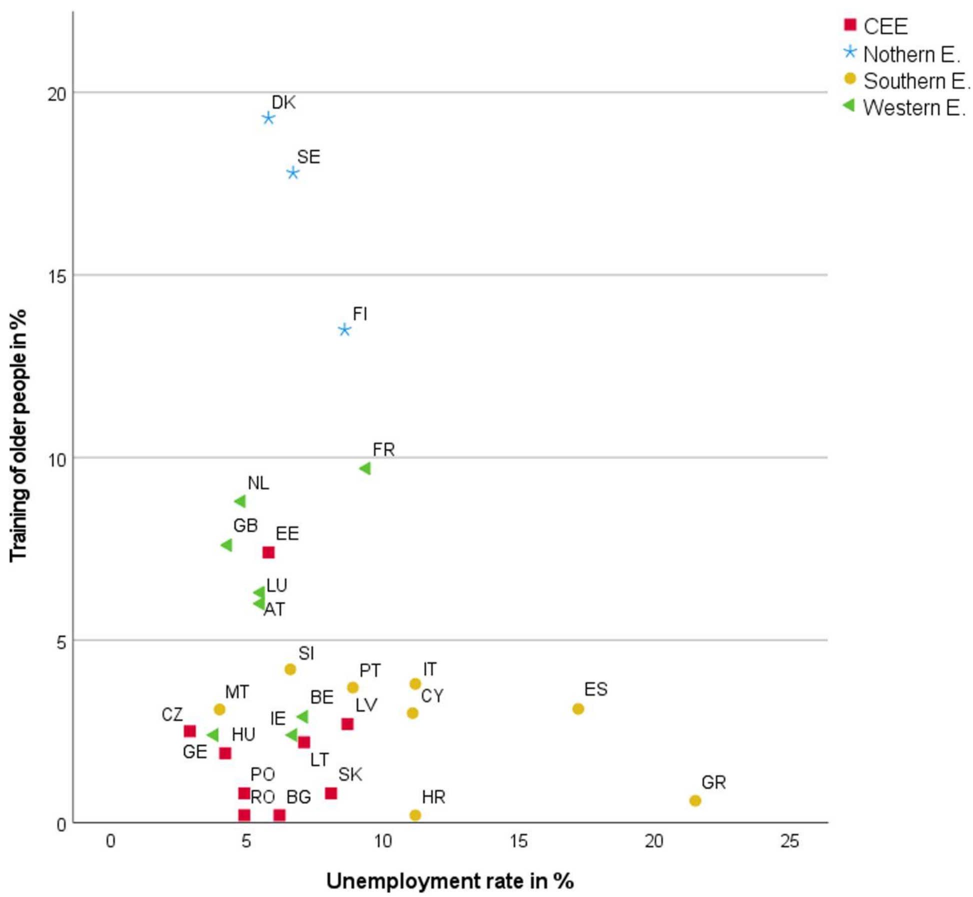

Figure 1. Values of macro-variables indicating labour market opportunities from 2017.

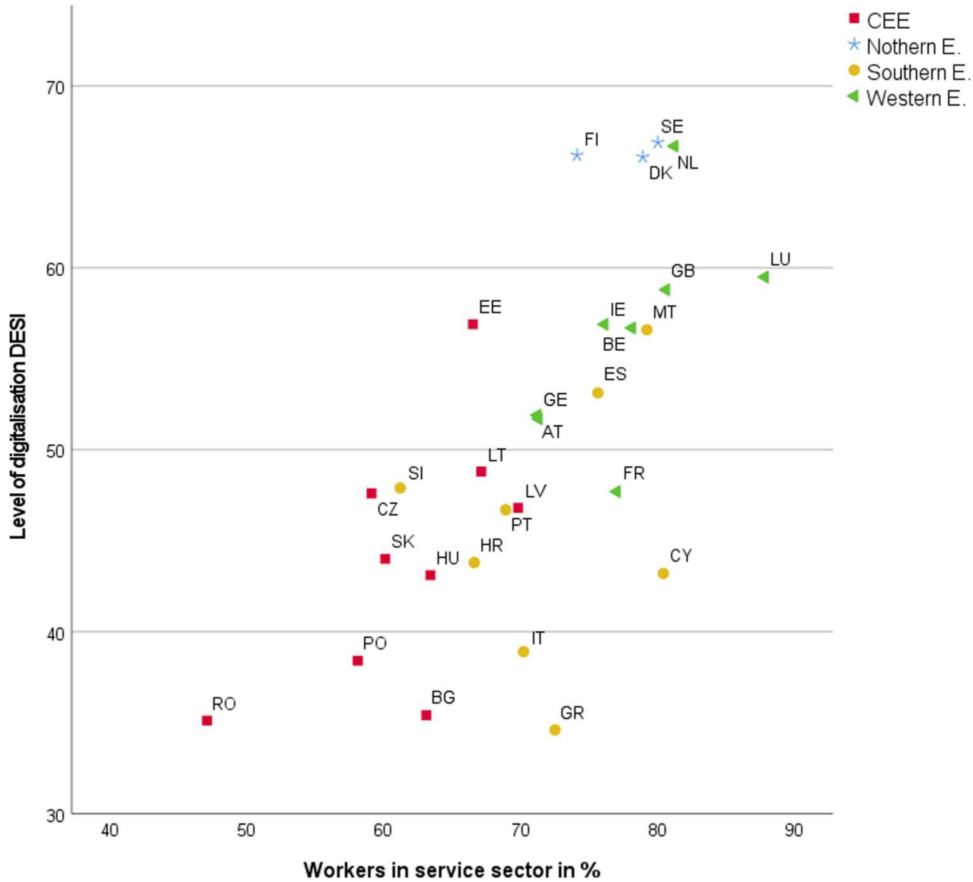

Figure 2. Values of macro-variables indicating the character of the economy from 2017.

allow estimating a logit model with one macro-variable (Bryan & Jenkins, 2016). Therefore, the paper tests two pairs of macro-factors indicating labour market opportunities (unemployment rate, training of older people) and the character of the economy (level of digitalisation, workers in the service sector). All six multilevel ordinal logistic regression models use the same individual predictors. Each of the three dependent variables was estimated in two models, one for each pair of macro-factors, all presented in Table 2.

Results

Descriptive statistics

The descriptive part of the analysis shows sample composition across two waves of data collection (Table 1) and the values of two pairs of contextual factors tested in separate sets of models (Figures 1 and 2). Additionally, Table A1 in the Appendix provides more context regarding the age composition of the workforce (Eurostat, 2024) and retirement age differences amongst EU countries (Trading Economics, 2024) to illustrate (a) some sample heterogeneities and (b) the increasing importance of older workers within

Table 2. Multilevel ordinal logistic regression for three dependent variables, unstandardised coefficients.

	Negative cognition		Negative affect		Positive affect	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Threshold 1 (between categories 1 and 2)	−1.220**	−2.811***	−3.741***	−3.846***	−1.339***	−3.223***
Threshold 2 (between categories 2 and 3)	0.243	−1.347*	−2.085***	−2.191***	0.171	−1.652**
Threshold 3 (between categories 3 and 4)	1.736***	0.145	−0.334	−0.440	2.603***	0.780
Age	−0.016**	−0.016**	0.002	0.001	0.010*	0.011*
Gender (woman)	−0.096*	−0.099*	0.212***	0.213***	−0.173***	−0.175***
Education	−0.019	−0.023*	−0.084***	−0.084***	0.062***	0.062***
Children in the household (yes)	−0.047	−0.038	0.035	0.037	−0.003	−0.003
Financial difficulties – never	−0.218*	−0.230*	−0.274**	−0.280**	0.336***	0.344***
From time to time	0.041	0.036	−0.326**	−0.327***	0.255**	0.255**
Most of the time (ref.)						
Type of job – self-employed	−0.569***	−0.562***	−0.402***	−0.400***	0.156+	0.155+
Managers and professionals	−0.428***	−0.421***	−0.162**	−0.164**	0.019	0.024
Employees in service sector	−0.619***	−0.609***	−0.506***	−0.510***	0.112	0.116
Manual workers (ref.)						
Internet usage – daily	0.093	0.101	−0.064	−0.071	0.359***	0.375***
Weekly or monthly	0.162+	0.166+	0.063	0.062	0.107	0.111
Less often or never (ref.)						
Type of community – large town	0.207***	0.202**	−0.209***	−0.210***	0.032	0.030
Middle town	0.106+	0.099+	−0.088+	−0.092	−0.104+	−0.103+
Rural area or village (ref.)						
EU membership – a good thing	0.181**	0.189**	−0.458***	−0.456***	0.484***	0.482***
Neither good nor bad	0.031	0.034	0.085	0.087	0.004	0.000
A bad thing (ref.)						
Unemployment rate	−0.009		0.038**		−0.008	
Training of older people	−0.040***		−0.056***		−0.001	
Level of digitalisation		0.000		−0.036***		0.004
Workers in service sector		−0.027***		0.024*		−0.030***
Random intercept variance	0.140	0.129	0.203	0.258	0.247	0.189
ICC	0.123	0.114	0.169	0.205	0.198	0.159
AIC	89,331.79	89,412.47	83,829.69	83,841.94	86,220.43	86,227.93
N	7,759	7,759	7,759	7,759	7,759	7,759

Notes: These calculations use data from Eurostat 2014 and 2017.
Significance levels: $+p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

the EU. Table 1 consists of three parts; distributions of the dependent variables, individual predictors, and contextual predictors. Negative cognition is not common (with only 14% of respondents viewing their job as mostly or entirely replaceable by a robot) but has increased over time (the percentage of answers *mostly or entirely replaceable* rose from 11 to 17 between the two data collections). The proportion of respondents who totally agree with the usefulness of robots declined from 30 to 24% whilst a strongly negative affect towards robots remained stable over time (and applied to 36% of respondents).

In terms of sample composition, most workers (70%) had no financial difficulties, 37% lived with at least one child, the most common type of job was manager or professional (35%), and a significant proportion resided in a small or middle town (41%). Most individual predictors remained stable over time, except for Internet usage (which increased) and opinion of the EU membership (with a sharp decrease in 'a bad thing' between 2014 and 2017).

Four macro-predictors are summarised by their mean values in Table 1. The mean unemployment rate for countries in the sample fell from 10 to 7% and the mean level of digitalisation rose by 8 points between the two waves of data collection. The proportion of older people recently receiving training and the proportion of workers in the service sector remained stable at approximate values of 5% and 71%. This overall description is further detailed by Figures 1 and 2, showing the values of the macro-variables for each country (in 2017; displaying the values only for one time point is clearer and the values within countries are fairly stable). The purpose of these figures is to show the grouping of the EU countries based on the characteristics studied and the association of two pairs of variables jointly analysed in regression analysis – unemployment with training (indicating labour market opportunities) and digitalisation with workers in the service sector (indicating the character of the economy).

Figure 1 illustrates that most of the EU countries had unemployment rates below 10%, except for some Southern European countries (with Greece and Spain having much higher values). Similarly, low variation is evident for the second variable, as only all three Northern European countries had more than 10% of older people recently participating in education and training. The relationship between these variables is moderately negative, with a lower unemployment rate being associated with more people in training (Pearson's $p = 0.24$) and its shape is non-linear (both visually and according to the test of linearity).

Figure 2 shows a higher variation for both variables – in absolute terms – with the DESI index ranging from 34.6 in Greece to 66.9 in Sweden and the percentage of workers in the service sector varying between 47.1 in Romania and 87.8 in Luxembourg. The association between the second set of macro-variables is much stronger (Pearson's $p = 0.63$) and linear, as a higher level of digitalisation is clearly linked to more workers in the service sector (especially in Northern European countries). Figure 2 also highlights a much more apparent grouping of countries by European regions.

Regression models for negative cognition

Table 2 shows models for three ordinal dependent variables with unstandardised coefficients (UCs) displayed; the interpretation in the text occasionally uses odds ratios (ORs) derived by exponentiating these UCs. The first part of Table 2 presents thresholds for the categories of the ordinal dependent variables introduced in the data section, whilst the last part displays model fit statistics. Model 1, which estimates the claim that the robot will replace the current job, shows that this attitude decreases with age (OR = 0.984), indicating that each additional year lowers the odds of more negative cognition by 1.6%. Negative cognition is more common amongst men (whose odds are 9% higher) and older workers with financial difficulties (those without difficulties have 20% lower odds of negative cognition). Level of education, children in the household, and frequency of Internet usage do not show any significant relationship with the dependent variable. In contrast, the expectation that a robot will replace their position is much more common amongst manual workers, those living in a large town/city, and those viewing the EU membership favourably.

Interestingly, the negative cognition is not influenced by the unemployment rate and occurs more often in countries where more older workers participate in training and education (the odds of negative cognition decrease by 4% for each percentage point of older workers recently receiving training). Finally, the ICC indicates that approximately 12% of the variance in the dependent variable can be attributed to differences between level-2 units.

Model 2 estimates the same outcome – negative cognition – with the coefficients for individual predictors being almost identical to those in Model 1. The coefficients for education and children vary slightly, but their substantive interpretation remains unchanged. The key distinction in the second model is the inclusion of a different pair of macro-predictors, this time reflecting the character of the economy. The level of digitalisation (DESI index) does not relate to the dependent variable. However, the coefficient for the proportion of the service sector is notable, with each additional percentage point of workers reducing the odds of feeling threatened by robots by 3%.

Regression models for negative affect

Model 3 predicts the negative affect, represented by the opinion that robots steal jobs. This indicator is similar to the dependent variable in Models 1 and 2, but (a) its slightly different meaning demonstrates how generalisable the results from the first pair of models are, and (b) its similarity shows the robustness of the findings above. Firstly, the coefficients for age, gender, and education differ substantially. Whilst the odds of believing that robots steal jobs do not vary by age, they are 24% higher (OR = 1.24) for women and 8% lower for each additional year of education. Next, negative affect is (similarly as negative cognition) more common amongst older workers with financial difficulties and manual workers. Finally, the odds of negative affect are 19% lower for individuals living in large towns and by 37% lower for those with a positive view of EU membership, which are the relationships opposite to those seen with negative cognition. This comparison of models could suggest that negative cognition reflects a realistic assessment of specific job situations, not necessarily linked to marginalised groups. In contrast, negative affect is associated with older workers living in precarious conditions.

All macro-predictors in Models 3 and 4 are statistically significant, which reinforces the interpretation provided in the previous paragraph. Firstly, a 1% increase in the unemployment rate raises the negative affect towards robots by 4%. Secondly, each additional percentage point of older workers that received training in a country decreases the negative affect by 5%. Thirdly, the opinion that robots steal jobs is also related to a lower DESI score and a higher proportion of workers in the service sector. Therefore, all contextual characteristics linked to negative affect reflect insecurity or precarity in some way. The importance of context it also demonstrated by the ICC = 0.205 for Model 4.

Regression models for positive affect

Model 5 predicts the positive affect, reflected by the opinion that robots help people. Its coefficients may have a direction opposite to those in Models 1–4 (especially compared with Models 3–4), if positive and negative attitudes towards digitalisation are connected to the same characteristics. Indeed, the positive affect is linked to men, the absence of financial difficulties, higher age, and a higher level of education (both continuous variables show a linear association), and these coefficients are mostly opposite to those associated with negative attitudes. However, the relationship of the opinion that robots help people with other variables gets more complex. The positive affect is not linked to the type of job or type of community. In contrast, it is strongly predicted by support for EU membership (OR = 1.62) and previously not significant frequent Internet usage (OR = 1.43).

The contextual factors in Models 5 and 6 are only associated with positive affect in one instance, namely, a negative relationship with the percentage of workers in the service sector. A tentative conclusion suggests that positive affect towards robots is partly predicted by good conditions (such as education and financial situation) and partly by what might be termed (techno)optimism, as indicated by frequent Internet usage, job in a technical area (partially supported by additional analyses), and a positive view of the EU. Of course, the findings require deeper interpretation and connections to previous research, which are addressed in the concluding section.

Conclusions and discussion

This article examines *attitudes towards digitalisation and automation of work*, a topic that currently resonates with society. Moreover, a growing population of workers is approaching or has already exceeded retirement age, highlighting the need for lifelong learning (not only) in digital skills. The study identifies groups of older workers and regions at risk of neglecting new technologies, which could help mitigate the digital divide in the future if effective policies target these at-risk groups of European citizens. The application of multilevel regression, grounded by the ecological perspective and focusing on inequalities framed by the theory of digital divide, illustrates how attitudes towards digitalisation are linked to several micro-, meso-, and macro-factors measured by available data. The main contribution of the paper lies in incorporating new factors associated with studied attitudes at several analytical levels, differentiating more measures of these attitudes, and making a strong theoretical argument.

Although the whole picture is not fully consistent, it seems that less privileged older workers from less privileged environments are more likely to resist technological innovation. This overall finding supports the application of the *theory of the digital divide* (Helsper, 2021; Van Dijk, 2006) together with the *ecological perspective* (Bronfenbrenner, 1977, 1986). Whilst the first approach is supported by more negative attitudes amongst workers disadvantaged technologically or otherwise, the latter emphasises the importance of other layers of reality beyond the individual level. Overall, the findings of this study are closer to those of Vasilescu et al. (2020), which apply the theory of the digital divide, than to other similar studies based on the *technology acceptance model* (Carradore, 2022; Turja & Oksanen, 2019).

This study has found that up to 61% of older workers lack any negative cognition about robots or AI. Simultaneously, up to 77% of participants agree that robots and AI help people. Conversely, approximately *70% of the participants agree that robots and AI can lead to unemployment*. Regarding the time dimension, the first two indicators became more negative between 2014 and 2017, with the third remaining stable. The large variation in attitudes may partially be accounted for by the hypothesised associations. These descriptive findings are themselves unique and not presented in existing studies (Carradore, 2022; Turja & Oksanen, 2019).

Workers who are female, have lower education, experience financial difficulties, and work manually tend to have more negative attitudes towards digitalisation in the labour market. Surprisingly, positive attitudes are weakly connected to higher age (H1c, H1d and H2b supported, H1a about age differences and H1b about gender differences not). Whilst most of the relationships are either intuitive or covered in the literature, the coefficient of age does not corroborate the findings of Vasilescu et al. (2020). The unexpected result may be explained by the fact that, whilst low-skilled individuals retire earlier, those better suited to the current labour market continue working and possibly distort sample representativeness (the cited study used a different age range of 15–65). The frequency of Internet usage, a very basic approximation of digital skills and techno-optimism, is related only to positive affect (H2a partially supported).

Then, *older workers who are supposedly benefiting more from the current changes* – those living in cities, supporting EU membership, and having higher education – have more negative cognition but *fewer negative and more positive affective attitudes* towards digitalisation (H2c and H3b supported partially). Therefore, these groups defined by micro- or meso-characteristics may have more realistic expectations whilst maintaining a more positive approach towards incoming changes. Moreover, this apparent disparity shows that including more dependent variables provides deeper insights into this topic. The findings show that the rural vs urban context still matters despite claims about 'the end of rural scholarship' (Bell, 2007). The attitude towards EU membership could be an indicator of a broader worldview, which is more positive amongst more privileged older workers. Finally, the study did not indicate a relationship between children in a household and the dependent variables (no support for hypothesis H3a).

The macro-contextual factors connected to *negative attitudes towards robots and AI are higher unemployment, lower availability of training for older workers, and lower levels of digitalisation*. The coefficients of these three variables are significant only for some dependent variables, but their effect is quite consistent given only 56 observations at this level of analysis (support for H4a, H4b, and H4c). The coefficients of the last macro-variable – the percentage of workers in the service sector – are all significant, but the negative association with positive cognition is seemingly opposite to the other two relationships. In this case, the prevalence of workers in sectors other than the service sector seems to have the same effect as education and town size; workers in service-oriented economies perceive possible risks of the digital economy but appreciate its overall benefits. Hence, previous cross-national differences identified by Turja and Oksanen (2019) were expanded with additional socio-economic explanations.

The study has several *limitations*, most of them common in observational studies. First, the results contain only associations, not causal links between variables. In particular, causal effects of macro-context are hard to identify. Second, only indicators measured at the individual level in the Eurobarometer could be studied as micro- and meso-factors, even though other characteristics of jobs or regions likely play a role as well. Third, the analysis focuses on attitudes, which are only an approximate identification of groups and contexts at potential risk. Fourth, the Eurobarometer has faced some critique for contextual effects, social desirability bias, and surface-level insights (Höpner & Jurczyk, 2015). Finally, the data are relatively old and were collected under circumstances different from those we observe today (with the mass inception of generative AI, etc.). Future research should address these limitations, particularly through other types of research design (qualitative, experimental, survey experiment, one-company study), which are needed to balance out the drawbacks of cross-national observational studies. At the same time, adapting the EU to the digital economy is inevitable, and this study provides a complex multilevel picture that expands the existing knowledge.

Identifying groups of workers at potential risk of inadequate adaptation to the digital economy can help in several applied areas. *A key aspect of preparing workers for turbulent changes in the labour market is informing them about the associated benefits*. The integration of robots or AI can simplify routine tasks. This step would allow more time to be allocated to the creative aspects of work, as also highlighted by Ivanov et al. (2020). On the other hand, employers should maintain as much transparency as possible when implementing workplace changes, which aligns with the existing research (Ivanov et al., 2020; Lawrence et al., 2017). Hence, the article can help to orient companies towards less problematic adaptation of technologies by pointing out which groups of workers approach these changes more negatively. Finally, it is necessary to develop public policies that restrict the effect of pessimistic attitudes towards new technologies and minimise the present digital divide, especially in areas of lifelong learning and the broad availability of adequate technologies.

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Data availability statement

The data provided by Eurostat are freely accessible. The final dataset and syntax can be obtained upon request.

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References

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, *33* (2), 3–30. https://doi.org/10.1257/jep.33.2.3

Allport, G. W. (1954). *The nature of prejudice*. Addison-Wesley.

Bechter, B., Brandl, B., & Lehr, A. (2022). The role of the capability, opportunity, and motivation of firms for using human resource analytics to monitor employee performance: A multi-level analysis of the organisational, market, and country context. *New Technology, Work and Employment*, *37* (3), 398–424. https://doi.org/10.1111/ntwe.12239

Bell, M. M. (2007). The two-ness of rural life and the ends of rural scholarship. *Journal of Rural Studies*, *23* (4), 402–415. https://doi.org/10.1016/j.jrurstud.2007.03.003

Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American Psychologist*, *32* (7), 513–531. https://doi.org/10.1037/0003-066X.32.7.513

Bronfenbrenner, U. (1986). Ecology of the family as a context for human development: Research perspectives. *Developmental Psychology*, *22* (6), 723–742. https://doi.org/10.1037/0012-1649.22.6.723

Bryan, M. L., & Jenkins, S. P. (2016). Multilevel modelling of country effects: A cautionary tale. *European Sociological Review*, *32* (1), 3–22. https://doi.org/10.1093/esr/jcv059

Carradore, M. (2022). People's attitudes towards the Use of robots in the social services: A multi-level analysis using eurobarometer data. *International Journal of Social Robotics*, *14* (3), 845–858. https://doi.org/10.1007/s12369-021-00831-4
Di Giacomo, D., Guerra, F., Perilli, E., & Ranieri, J. (2020). Technophobia as emerging risk factor in aging: Investigation on computer anxiety dimension. *Health Psychology Research*, *8* (1), 1–4. https://doi.org/10.4081/hpr.2020.8207
Domini, G., Grazzi, M., Moschella, D., & Treibich, T. (2022). For whom the bell tolls: The firm-level effects of automation on wage and gender inequality. *Research Policy*, *51* (7), 104533. https://doi.org/10.1016/j.respol.2022.104533
Eurofound. (2012). *Income from work after retirement in the EU*.
European Commission. (2018). *Eurobarometer 82.4 (2014)*. GESIS Data Archive. https://doi.org/10.4232/1.13044
European Commission. (2021a). *Eurobarometer 87.1 (2017)*. GESIS Data Archive. https://doi.org/10.4232/1.13738
European Commission. (2021b). *The Digital Economy and Society Index (DESI) 2021 Thematic chapters*. https://digital-strategy.ec.europa.eu/de/node/9773
Eurostat. (2024). *Employment and activity by sex and age - annual data*. https://doi.org/10.2908/lfsi_emp_a
Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019
Hecklau, F., Orth, R., Kidschun, F., & Kohl, H. (2017). Human resources management: Meta-study-analysis of future competences in industry 4.0. *European Conference on Management, Leadership & Governance*, 163–174.
Helsper, E. (2021). *The digital disconnect: The social causes and consequences of digital inequalities* (1st ed.). SAGE.
Höpner, M., & Jurczyk, B. (2015). How the Eurobarometer blurs the line between research and propaganda. *MPIfG Discussion Paper*, *15* (6), 1–19. http://www.mpifg.de/pu/mpifg_dp/dp15-6.pdf
Ivanov, S., Kuyumdzhiev, M., & Webster, C. (2020). Automation fears: Drivers and solutions. *Technology in Society*, *63*, 101431. https://doi.org/10.1016/j.techsoc.2020.101431
Klarsfeld, A., Carillo, K., Cachat-Rosset, G., Saba, T., & Marsan, J. (2024). Does the welfare regime impact the telework gender stress gap? *New Technology, Work and Employment*, *39* (1), 168–195. https://doi.org/10.1111/ntwe.12287
Lawrence, M., Roberts, C., & King, L. (2017). *Managing Automation: Employment, inequality and ethics in the digital age*.
Makó, C., & Illéssy, M. (2020). Automation, creativity, and the future of work in Europe: A comparison between the old and new member states with a special focus on Hungary. *Intersections East European Journal of Society and Politics*, *6* (2), 112–129. https://doi.org/10.17356/IEEJSP.V6I2.625
Maltby, T., de Vroom, B., Mirabile, M. L., & Øverbye, E. (2017). *Ageing and the transition to retirement: A comparative analysis of European welfare states*. Routledge.
Marinoudi, V., Lampridi, M., Kateris, D., Pearson, S., Sørensen, C. G., & Bochtis, D. (2021). The future of agricultural jobs in view of robotization. *Sustainability*, *13* (21), 1–15. https://doi.org/10.3390/su132112109
McCann, R. M., & Keaton, S. A. (2013). A cross cultural investigation of age stereotypes and communication perceptions of older and younger workers in the USA and Thailand. *Educational Gerontology*, *39* (5), 326–341. https://doi.org/10.1080/03601277.2012.700822
McClure, P. K. (2018). "You're fired," says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. *Social Science Computer Review*, *36* (2), 139–156. https://doi.org/10.1177/0894439317698637
Schaupp, S. (2022). Algorithmic integration and precarious (Dis)Obedience: On the co-constitution of migration regime and workplace regime in digitalised manufacturing and logistics. *Work, Employment and Society*, *36* (2), 310–327. https://doi.org/10.1177/09500170211031458

Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information and Management*, *44* (1), 90–103. https://doi.org/10.1016/j.im.2006.10.007
Snell, D., & Gekara, V. (2023). Re-examining technology's destruction of blue-collar work. *New Technology, Work and Employment*, *38* (3), 415–433. https://doi.org/10.1111/ntwe.12259
Trading Economics. (2024). *Retirement age of men and women*. https://tradingeconomics.com/country-list/retirement-age
Turja, T., & Oksanen, A. (2019). Robot acceptance at work: A multilevel analysis based on 27 EU countries. *International Journal of Social Robotics*, *11* (4), 679–689. https://doi.org/10.1007/s12369-019-00526-x
UNECE. (2019). *Active Ageing Index 2018: Analytical Report* (Issue ECE/WG.1/33).
Van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics*, *34* (4–5), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004
Vasilescu, M. D., Serban, A. C., Dimian, G. C., Aceleanu, M. I., & Picatoste, X. (2020). Digital divide, skills and perceptions on digitalisation in the European union - towards a smart labour market. *PLoS One*, *15* (4), 1–39. https://doi.org/10.1371/journal.pone.0232032
Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, *54* (6), 1063–1070. https://doi.org/10.1037/0022-3514.54.6.1063
World Bank. (2022). *World bank open data*. https://data.worldbank.org/
Xi, W., Zhang, X., & Ayalon, L. (2022). The framing effect of intergenerational comparison of technologies on technophobia Among older adults. *Journals of Gerontology - Series B Psychological Sciences and Social Sciences*, *77* (7), 1179–1185. https://doi.org/10.1093/geronb/gbab199
Zacher, H., Esser, L., Bohlmann, C., & Rudolph, C. W. (2019). Age, social identity and identification, and work outcomes: A conceptual model, literature review, and future research directions. *Work, Aging and Retirement*, *5* (1), 24–43. https://doi.org/10.1093/workar/way005

Appendix

Table A1. Proportion of the active labour force comprising the age group 55–64 along with the most recent statutory retirement age for each country.

Country	Age group 55–64 in 2014 (% of labour force)	Age group 55–64 in 2017 (% of labour force)	Retirement age for men	Retirement age for women
Austria	11.8	14.2	65	60.5
Belgium	13.0	15.3	65	65
Bulgaria	17.5	18.5	64.58	62.17
Croatia	13.5	14.7	65	63.5
Cyprus	12.6	14.5	65.5	65.5
Czech Republic	15.6	16.2	64.33	64.33
Denmark	17.0	18.5	67	67
Estonia	17.9	18.9	64.75	64.75
Finland	19.0	19.7	64.5	64.5
France	14.8	16.1	62.5	62.5
Germany	18.7	20.5	66	66
Greece	11.6	13.7	67	67
Hungary	13.8	15.2	65	65
Ireland	13.2	14.5	66	66
Italy	14.9	17.4	67	67
Latvia	16.9	19.2	64.75	64.75
Lithuania	16.4	20.3	64.67	63.33
Luxembourg	10.6	9.9	65	65
Malta	13.0	13.2	64	64
Netherlands	17.2	18.9	67	67
Poland	14.3	15.3	65	60
Portugal	14.1	16.7	66.33	66.33

(*Continued*)

Table A1. Continued.

Country	Age group 55–64 in 2014 (% of labour force)	Age group 55–64 in 2017 (% of labour force)	Retirement age for men	Retirement age for women
Romania	12.2	12.5	65	62
Slovakia	13.6	15.3	63	63
Slovenia	11.5	13.4	60	60
Spain	13.3	15.6	66.5	66.5
Sweden	18.4	18.4	63	66
UK	n.a.	n.a.	66	66

Notes: The age proportion are from the Eurostat file *lfsi_epm_a*. The latest retirement age data is from the *Tradingeconomics.com* database.