Technological Forecasting & Social Change 198 (2024) 122998

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

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

How digital technology affects working conditions in globally fragmented production chains: Evidence from Europe

Aleksandra Parteka *, Joanna Wolszczak-Derlacz, Dagmara Nikulin

Gdańsk University of Technology, Faculty of Management and Economics, Narutowicza 11/12, 80-233 Gdańsk, Poland

ARTICLE INFO

JEL classification:
F1
F6
J8
O3

Keywords:
Digital technology
Working conditions
GVC
Global value chains
artificial intelligence
AI

ABSTRACT

This paper uses a sample of over 9 million workers from 22 European countries to study the intertwined relationship between digital technology, cross-border production links and working conditions. We compare the social consequences of technological change exhibited by three types of innovation: computerisation (software), automation (robots) and artificial intelligence (AI). To fully quantify work-related wellbeing, we propose a new methodology that amends the information on remuneration by reference to such non-monetary factors as the work environment (physical and social), career development prospects, or work intensity. First, we show that employee wellbeing is related to the *type* of technological exposure. Employees in occupations with a high degree of software or robot exposure face worse working conditions – contrary to highly AI exposed occupations. Thus, we find that AI technologies differ from previous waves of technological progress - also in relation to workers' wellbeing. Additionally, we show that the relationship between digital technology and working conditions weakly depends on participation in global production chains.

1. Introduction

The economic literature has raised many questions in relation to the labour market implications of dynamically changing production systems. Technological progress has triggered a debate on how the substitution of automated processes for human skills affects workers (among countless others: Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2020; Frey and Osborne, 2017; Graetz and Michaels, 2018; Brynjolfsson et al., 2018; Goos, 2018). Trade with cheap-labour countries has raised fears of job losses or downward wage pressure in developed economies (Autor et al., 2014; Baumgarten et al., 2013; Ebenstein et al., 2014; Egger et al., 2015; Hummels et al., 2018; Parteka and Wolszczak-Derlacz, 2020; Shen and Silva, 2018; Cardoso et al., 2021). However, the latest wave of technological progress (including digitalisation, automation and the development of AI: Agrawal et al., 2019; WIPO, 2019; UNIDO, 2020; Gruetzemacher et al., 2021), together with intense cross-country production links within Global Value Chains, GVCs (Baldwin, 2012; Baldwin and Venables, 2013; Timmer et al., 2015; Antràs and Chor, 2022), also has another important dimension, namely the impact on working conditions.

This paper assesses the links between progress in digital technology and working conditions in globally integrated production chains. Our aim is to fill the research gap regarding the measurement of working conditions (i.e. not only through wages, but also other non-monetary aspects of work quality) and distinguishing the effects of particular *types* of digital technologies, including the latest AI solutions, on employee well-being.

Specifically, our contribution is three-fold. First, while evaluating labour conditions, we go beyond the purely monetary approach. The correlation between income and job satisfaction is far from perfect (Clark, 2015), and the socio-economic literature postulates the need to consider non-wage job dimensions in a multidimensional analysis of labour quality (Mira, 2021; Gallie et al., 2012; Fleurbaey, 2015; Nikulin et al., 2022; OECD, 2017). Along with the transformation of the task content of jobs (Autor and Handel, 2013; Frey and Osborne, 2017; Acemoglu and Restrepo, 2019; Brynjolfsson and Mitchell, 2017; Brynjolfsson et al., 2018), advanced technology has altered the work context and job satisfaction. Some of the changes have been beneficial, such as the use of machines in harmful environments and the automation of dangerous tasks (Gisbert et al., 2014). On the detrimental side, increasing digitalisation impacts various aspects of workers' satisfaction not directly related to remuneration (Lane and Saint-Martin, 2021), affecting their mental health, productivity, job satisfaction, and risking burnout or work-life conflict (Badri et al., 2018; Berg-Beckhoff et al., 2017; Tarafdar et al., 2007; Salanova et al., 2014; Mahapatra and Pati, 2018). We thus take a holistic, sociological approach to studying employee wellbeing in a

* Corresponding author.
E-mail addresses: aparteka@zie.pg.edu.pl (A. Parteka), jwo@zie.pg.gda.pl (J. Wolszczak-Derlacz), dnikulin@zie.pg.gda.pl (D. Nikulin).

https://doi.org/10.1016/j.techfore.2023.122998
Received 19 November 2021; Received in revised form 19 October 2023; Accepted 6 November 2023
Available online 18 November 2023

multidimensional setting (Ledić and Rubil, 2021; Mira, 2021; Gallie et al., 2012; Fleurbaey, 2015; Nikulin et al., 2022; OECD, 2017). Conceptually, our analysis of working conditions is based on the theoretical framework of wellbeing in the spirit of the Job Demand-Resources model (Bakker and Demerouti, 2007; Lesener et al., 2019). Following Ledić and Rubil (2021), we propose a methodological innovation, matching wage data with the multiple non-wage dimensions of job quality such as: the physical and social environment at work, work intensity, the quality of working time, skills and discretion, and prospects.[1]

Second, we extend the literature on the implications of technological progress for individual workers by examining diverse technology types: ICT, robots and AI.[2] The way they impact the quality of employment is likely to be different because they have followed different waves of development (Agrawal et al., 2019; UNIDO, 2020; Gruetzemacher et al., 2021), are targeted at different types of tasks (Webb, 2020; Autor and Handel, 2013; Frey and Osborne, 2017; Acemoglu and Restrepo, 2019; Brynjolfsson and Mitchell, 2017; Brynjolfsson et al., 2018) and operate through different channels. In particular, we assess how AI technological solutions may differ from previous waves of automation because while the literature on the labour market implications of computerisation and robotisation is abundant (among many others: Acemoglu and Restrepo, 2018, 2020; Goos et al., 2014; Goos, 2018), systematic research dealing explicitly with the relationship between AI and employee wellbeing is still relatively scarce.[3] This shortcoming is explained in part by the general lack, until recently, of analytical tools to measure AI phenomena. However, progress in the quantification of AI solutions for economic and social research (OECD, 2022; Baruffaldi et al., 2020) has now broken new ground for AI-focused labour-market analysis (Lane and Saint-Martin, 2021; Agrawal et al., 2019). We use the latest measures of the exposure of tasks to software, robots and AI (Webb, 2020) to compare their potentially diverse links with employee wellbeing.

Third, we do not isolate the link between technological progress and working conditions from changes in business models due to cross-border production fragmentation. The development of digital technologies and GVCs are intertwined (Baldwin, 2012, 2016; Basco and Mestieri, 2018). Value chains simply cannot be ignored: OECD reports that "70% of international trade involves a variety of transactions where services, raw materials, parts and components are exchanged in global value chains (GVCs) across countries".[4] Approximately one-fourth of European manufacturing production depends on intermediate products produced in other countries (Parteka and Wolszczak-Derlacz, 2020). The labour market implications of globalised production have been widely examined, but almost always in order to quantify the effects on wages (Baumgarten et al., 2013; Ebenstein et al., 2014; Shen and Silva, 2018; Geishecker and Görg, 2013; Parteka and Wolszczak-Derlacz, 2019, 2020; Cardoso et al., 2021; Szymczak and Wolszczak-Derlacz, 2022), jobs and labour demand (Goos et al., 2014; Franssen, 2019; Autor et al., 2014; Egger et al., 2015; Hummels et al., 2018; Szymczak and Wolszczak-Derlacz, 2022), or productivity (Amador and Cabral, 2015). Studies on the social aspects of work within GVCs are less common (Gimet et al., 2015; Milberg and Winkler, 2011; Nikulin et al., 2022), and in many cases deal with problems typical of developing countries (Delautre et al., 2021; Lee et al., 2016; Nadvi et al., 2004; Rossi, 2013). Surprisingly, the literature on job quality and GVCs has rarely examined the case of European workers (Nikulin et al., 2022); we fill this gap by using a broad European sample.

In short, we propose a multi-country analysis of the links between modern technologies and the wellbeing of workers in Europe, within a unified micro-level analytical framework. We build a rich employee-level dataset, with information on socio-demographic characteristics, wages and some non-income aspects of working conditions, technology-related features of occupations and industries, as well as GVC indicators. We provide evidence that is neither country- nor industry- specific: the sample encompasses over 9 million manufacturing and service workers in 22 European countries, performing diverse tasks that differ in both the degree and type of technology content.

The rest of the paper is structured as follows. In Section 2 we review the literature on the relationship between technology and employee wellbeing, focusing on effects driven by digital developments. Section 3 presents the data and the main descriptive evidence, concerning the heterogeneity of working conditions in Europe and its relationship with technological exposure. Section 4 presents the econometric results, and Section 5 concludes.

2. Digital technology and working conditions – Literature review

We place our research in the context of the wealth of literature on interactions between technology and labour markets. Given the extremely rapid (and unforeseeable - Gruetzemacher et al., 2021) technological development of recent decades (Aghion et al., 2019), numerous studies have addressed the common anxiety over wages and/or employment pressure (for a review see Goos, 2018) and technologically-driven job displacement: workers performing routine tasks are particularly vulnerable because their jobs are easy to automate (Frey and Osborne, 2017). Changes in labour demand have been conceptualised through the hypothesis of skill-biased technological change (SBTC) and the related framework of routine-based technological change (RBTC): Acemoglu and Autor (2011); Autor et al. (2003); Goos et al. (2014). Empirical findings confirm this view, pointing towards technology-forced displacement of routine-intensive tasks in many developed countries, particularly the United States (Autor et al., 2003; Autor and Handel, 2013; Autor and Dorn, 2013; Frey and Osborne, 2017) and Western Europe (the case of the EU-15 has been analysed by Goos et al., 2014 and Marcolin et al., 2016; the case of Germany, by Spitz-Oener, 2006). These empirical studies on the effects of automation/robotisation typically rely on the classification of workers according to the degree of routine content of the tasks characteristic of a given occupation.[5] This approach views jobs as bundles of tasks (Autor et al.,

[1] These features can be quantified via the indicators of the European Working Conditions Surveys (EWCS) (Eurofound, 2021) - See Section 3.1. Table S2 (in Supplementary materials) for details on job quality indices derived from EWCS and adopted in our analysis.

[2] In terms of definition, we follow the OECD Council on Artificial Intelligence, defining AI as a "(…) machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy" (Baruffaldi et al., 2020: 11). The boundaries between AI technology and other digital technologies can be blurred but while ICT is typically pre-programmed, solutions based on AI are capable of learning and improving. Webb (2020) considers a computer program to be software (in contrast to AI) if every action it performs has been specified beforehand by a human.

[3] Brynjolfsson et al. (2018); Felten et al. (2019) and Webb (2020) assess AI-exposure of jobs.

[4] file:///C:/Users/Ola/Downloads/Trade%20Policy%20Implications%20of%20Global%20Value%20Chains%20(1).pdf [assessed on 12 October 2023]

[5] Indices of occupation-specific routinisation (i.e., routine content of jobs) are available for the US (Autor et al., 2003; Acemoglu and Autor, 2011) and also for broader sets of countries (Marcolin et al., 2016; Lewandowski et al., 2022 constructing routine task intensity index; Bisello et al., 2021). In the recent literature on the AI content of jobs, similar metrics have been developed, by combining the information contained in job task descriptions (e.g., from the US Department of Labor's O*NET) with the texts of AI patents (Webb, 2020) or by measuring "suitability for machine learning" (Brynjolfsson et al., 2018). Felten et al. (2019) proposed an AI Occupational Impact measure that matches specific AI applications (image recognition, translation, the ability to play strategic games) with workplace abilities and occupations.

2003) and differs from the classic division of workers according to broad skill/education categories (Acemoglu and Autor, 2011).

However, there are multiple channels through which technology affects employee wellbeing and the theoretical explanation of factors affecting working conditions is complex. The literature suggests referring to the multidimensional frames rooted in the Job Demands-Resources (JD-R) model (Bakker and Demerouti, 2007; Lesener et al., 2019). The driving forces predicting employee personal wellbeing stem from the interplay between the job demands workers are exposed to (physical, psychological, social and organisational aspects of the job, such as high work pressure, emotional demands, role ambiguity, poor physical environment or demanding interactions with clients) and job resources (such as social support, performance feedback, autonomy, achieving work goals, stimulating personal growth). Importantly for our study, the JD-R approach may help to explain conceptually the link between working conditions and various technology types. Such links are rather ambiguous. Among the ICT-focused JD-R studies, Kim and Christensen (2017) show that the personal use of technology at work can have both negative and positive effects on organisational outcomes. Computerisation causes technostress (adverse effect of ICT use): Mahapatra and Pati (2018) adopted JD-R frames to investigate five individual technostress creators (techno-overload, techno-invasion, techno-complexity, techno-insecurity and techno-uncertainty), finding that techno-invasion (the blurred boundaries between work and home) and techno-insecurity (the fear of job loss due to automation processes) lead to job burnout. Carlson et al. (2017) focused on technology-based job autonomy, overload, monitoring and turnover frequency, showing that the role of technology is mixed: it may enhance job satisfaction (through increased job autonomy and greater job engagement), but also decrease it (due to technology job overload and increased job tension). Nuutinen et al. (2022) adopt the JD-R framework to analyse the effect of job resources on employee wellbeing through technology-enabled performance (TEP) and find a positive mediating role from work engagement. Automation processes (i.e., robotisation) can also lead to diverse effects on the work of employees, because Robotic Process Automation (RPA) decreases physically straining job tasks, but at the same time, RPA increases the feeling of alienation and is negatively associated with autonomy and task variety, leading to decreased employee work engagement (Peeters and Plomp, 2022).

Moreover, the literature not based on the JD-R framework also reveals a great complexity of working conditions - technology connections, varying by technology type (see the literature review summarised in the Appendix in Table 1A). The effects of ICT adoption on working conditions has been addressed intensively in the health and safety literature (Badri et al., 2018). Innovative labour risk prevention applications exploiting digital technologies (Gisbert et al., 2014) confirm the potential of these technologies for detecting risks to employee health and safety in critical environments (e.g., machining, handling and assembly factories). However, at the same time, a major threat to wellbeing is posed by internet addition, technostress, blurred boundaries between work and personal life, and work overload (Tarafdar et al., 2007; Salanova et al., 2014; Berg-Beckhoff et al., 2017). Among the studies on working conditions and automation, Antón et al. (2023) revealed its negative link with work intensity, Turja et al. (2022) found lower intrinsic job satisfaction in a robotised workplace, while Damiani et al. (2020) revealed adverse effects of robots on workers in industries characterised by high/low cumulativeness of knowledge. However, the application of AI-focused measures (Brynjolfsson et al., 2018; Felten et al., 2019; Webb, 2020) leads to different conclusions yet from those postulated by studies on previous technologies (ICT or robots) that underlined mainly the substitution effect between the workers and the machines (Acemoglu and Restrepo, 2018, 2020). Webb (2020) argues that in contrast to software and robots, AI is targeted at high-skilled tasks because while "robots perform 'muscle' tasks and software performs routine information processing, AI performs tasks that involve detecting patterns, making judgements, and optimisation" (Webb, 2020: 3). AI technologies are able to automate a wide range of tasks, including non-routine cognitive tasks (Brynjolfsson et al., 2018; Brynjolfsson and Mitchell, 2017), and "AI exposure" is not exactly the same as the danger of being *replaced* by AI. Workers performing highly demanding jobs and those in high-skilled occupations (chemical engineers, for instance), highly exposed to AI (Webb, 2020), might even benefit from the technical capabilities of machine learning and see their work complemented by AI solutions (Lane and Saint-Martin, 2021: 23). Moreover, AI may be used to manage employees through employee engagement, mainly by motivating and controlling. However, to analyse the exact effect of AI-driven systems on job satisfaction one has to take into consideration such issues as trust, perceived risk or fair play (see e.g., Hughes et al., 2019).

Another stream of literature related to our analysis refers to technological progress as one of the forces altering the global structure of production. The so-called "second unbundling" added the international dimension to domestic supply chains typical of the first unbundling (Baldwin, 2012; Baldwin and Venables, 2013): the ICT revolution made it possible to coordinate complexity at a distance and to offshore labour-intensive manufacturing stages to remote countries with lower labour costs. While offshoring was viewed as the successor to the industrial revolution (Blinder, 2006), the third unbundling of globalisation, driven by such solutions as telerobotics or telepresence (enabling workers in one country to perform service tasks in another), is the perspective that is now gaining traction (Baldwin, 2016). Further development of AI technologies may open up completely new possibilities, difficult indeed to forecast (Gruetzemacher et al., 2021). Worker-level effects of GVCs differ from the pressure due to traditional trade, where production processes do not cross national borders (Szymczak and Wolszczak-Derlacz, 2022). Numerous studies have assessed the labour market implications of production fragmentation (offshoring) in conjunction with the impact of technology - mainly by identifying which categories of workers are most endangered due to the type of tasks they perform (Baumgarten et al., 2013; Ebenstein et al., 2014; Shen and Silva, 2018; Goos et al., 2014; Parteka and Wolszczak-Derlacz, 2019, 2020; Autor et al., 2015; Egger et al., 2015; Hummels et al., 2018). Unsurprisingly, occupations consisting mainly of repetitive (routine-intensive) tasks are more susceptible to be displaced or to be subjected to downward wage pressure. The effects of trade and automation are intertwined: measures of offshorability (Blinder, 2009; Blinder and Krueger, 2013) are strongly related to the degree of job routinisation (Autor et al., 2003; Autor and Handel, 2013) and the probability of computerisation (Frey and Osborne, 2017). However, the literature focusing explicitly on working conditions broadly understood (not just wage or employment prospects), and the way they are jointly affected by the development of digital (especially AI) technologies and GVC proliferation, is lacking. In the next section we describe how we intend to fill this gap.

3. Methodological setting and descriptive evidence

3.1. Dataset

For the purpose of our analysis we build a rich employee-level dataset, containing information of workers' socio-demographic characteristics, wages, several other aspects of working conditions, and GVC- and technology-related features of occupations/industries. The analysis covers over 9 million workers in 22 European countries observed around 2015.[6] The Appendix contains the list of countries (Table 2A) and industries (Table 3A). Concerning the key characteristics of the analysed

[6] This date reflects the availability of data on working conditions: the EWCS survey is conducted every five years; at the time we wrote this paper the latest wave was from 2015. EWCS 2020 field work was halted due to COVID. The European Working Conditions Telephone Survey 2021 was released on 29th November 2022 (when we revised and finished our analysis).

sample, i.e., the structure of observations by country, gender, age, job experience and contract type (see the detailed data in Table 5A): the sample has equal gender representation (50 % males, 50 % females), the analysed workers belong mainly to the 'medium' age category (30–49, 52 % of the sample), most of them (above 80 %) have at least medium education and work full-time, while two-thirds are employed in the private sector. Job experience varies and is long (or very long) in the case of 37 % (or 20 %) of the employees in the sample.

Individual worker is the unit of analysis. In line with current economic labour market analysis (Hummels et al., 2018), our dataset provides information at different levels of detail (country, sector, occupation, individual) and is constructed by merging statistics from multiple sources. The Supplementary materials describe in detail the key original data sources (Table S1), namely: SES (Structure of Earnings Survey - 2014),[7] EWCS (European Working Conditions Survey - 2015), (WIOD, 2021), PWT 9.1 (Penn World Table) and ICTWSS (Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts). The quantification of exposure to digital technologies is performed at two levels. First, we employ the digital taxonomy of industries from Van Ark et al. (2019), dividing sectors into digital-producing and (least or most) digital-intensive using categories[8] (Table 3A). Secondly, we combine the micro-level information contained in SES and EWCS with three alternative indices used to classify workers according to the digital exposure of their jobs to software, robots and AI (Webb, 2020).[9] The mergee of the data coming from these sources was possible thanks to the cross-identification of worker occupation[10] (in SES, EWCS and Webb, 2020), sector of employment (in SES, Van Ark et al., 2019, WIOD) and country (in SES, WIOD, PWT and ICTWSS). Given the cross-sectional structure of the dataset (tracing workers across time, is impossible due to the cross-sectional character of EWCS and SES), our results should be interpreted with caution, due to differences in working conditions across European workers at a given point in time.

The quantification of working conditions is no easy task. To fully account for the complexity of work quality satisfaction and its non-wage dimensions (in line with Ledić and Rubil, 2021), we link the information on remuneration with other aspects through combining the job quality indices from EWCS and SES data on wages.[11] We proxy the working conditions (*WC*) faced by every worker in the dataset by:

$$WC_{ioc}^{k} = wage_i \times \frac{JQ_{oc}^{k}}{\frac{\sum_{i=1}^{N_c} JQ_{oc}^{k}}{N_c}} \tag{1}$$

where: *JQ* is the job quality index of type *k* typical for occupation *o* in country *c,* and $wage_i$ is the hourly wage of worker *i* (in US dollars). The set of *k* aspects of job quality, assessed relative to the country mean, includes: physical environment, work intensity, working time quality, social environment, skills and discretion, and prospects - see Table S2 in Supplementary materials for details on the exact content of *JQ* and the method of quantification. N_c denotes the total number of workers in country *c*. Such a composite *WC* measure (1) can be higher (or lower) than the original (monetary) wage, depending on whether an individual performs a job of higher (lower) quality than other workers in the same country. For example, if a worker is employed in an occupation characterised by a social environment 10 % above the country average (based on survey results), we assume that her/his working conditions (taking account of both monetary remuneration and social environment) are 10 % better than they would be due purely to wages.

Finally, to capture the extent of involvement in globally fragmented production, we use industry-level GVC indicators (based on WIOD input-output data, Timmer et al., 2015), matched with the rest of the data according to the sector of activity (NACE Rev. 2).[12] In the benchmark analysis, GVC intensity is measured by the share of foreign value added in exports (FVA/Export; Koopman et al., 2014), obtained from the decomposition of gross exports (Wang et al., 2013). That is, GVC intensity measures the value added derived from imported inputs, used in the production of goods or services (intermediate or final) and then exported. Alternative GVC measures: *OFF* - classic offshoring, i.e., the ratio of intermediate imports to total sectoral output (Feenstra and Hanson, 1999; Geishecker and Görg, 2013; Goos et al., 2014); or *GII* - global import intensity of production (Timmer et al., 2016; Szymczak et al., 2022) are adopted for the robustness analysis.

3.2. Job quality versus technological exposure and GVC involvement

Our database allows us to examine the relationship between alternative indices of job quality from EWCS and the different types of technology used intensively in a given job. Fig. 1 shows the correlation of occupational exposure to software, robots and AI (Webb, 2020) with various non-wage aspects of job quality. Greater exposure to all three types of technology is correlated positively with the quality of the social environment (Fig. 1, panel A), and negatively with the physical environment (Fig. 1, panel C) and work intensity (Fig. 1, panel D). Overall, greater exposure to AI is accompanied by better prospects and higher levels of skills and discretion, but also greater work intensity and a poorer physical environment. For some aspects of job quality, however, correlations differ between exposure to AI technologies and exposure to computerisation or robotisation. For instance, skills and discretion (Fig. 1, panel B) and prospects (Fig. 1, panel E) are correlated negatively

[7] Access to the micro-level Structure of Earnings Survey (SES) data is free of charge, but an application is required. The data was granted by Eurostat upon acceptance of a research proposal (Proposal 225/2016-EU-SILC-SES).

[8] The classification of Van Ark et al. (2019) draws upon Calvino et al. (2018) and is based on such aspects as: the share of tangible and intangible ICT investment; the share of intermediate purchases of ICT goods and services; the stock of robots per hundred employees; the share of ICT specialists in total employment; and the share of turnover from online sales. In particular, Van Ark et al. (2019) separate out: electrical and optical equipment, publishing, audio-visual and broadcasting activities, telecom services and IT and other information services, classifying them as "producing digital goods and services" (DP). The earlier taxonomy of Van Ark et al. (2016) is based only on ICT service and investment intensity.

[9] Alternative classifications of occupations according to their AI content have been proposed by Brynjolfsson et al. (2018) and Felten et al. (2019). We rely on the classification of Webb (2020) because it allows us to confront different technologies: software, robots and AI. Webb's occupational exposure scores for a given technology *t* (computers, robots, AI) express the intensity of patenting activity in technology t directed towards the tasks in that occupation.

[10] The occupation level corresponds to a two-digit ISCO-08 code (this level of aggregation reflects the level of detail in EWCS). We use B23 variable from SES. The conversion from Webb's list of occupations to our ISCO-08 codes was performed by using first his crosswalk (occ1990dd) from O*NET, and then the Bureau of Labor Statistics' crosswalk from O*NET to ISCO_08. The passage to the sector and country level data was possible thanks to the use of NACE and COUNTRY variables in SES.

[11] Such an approach is also supported by the examination of the correlation matrix between separate job quality indicators and wages (Table 4A in the Appendix): JQ indices are loosely related to wages (see the column in grey): this is especially so for such aspects of job quality as social environment and working time quality, and, to a lesser extent, physical environment and work intensity.

[12] In some cases, we had to combine the original WIOD sectors into broader categories (listed in Table 3A), to assure their correspondence with the sectoral information present in SES. For such industry groupings, we computed an average of underlying industries' GVC measures (e.g., share of foreign value added in exports).

with robot/software exposure but positively with AI exposure. This suggests that the connection between working conditions and the digitalisation of the work environment depends on the specific type of technology installed in a given occupation.

Given that our analysis combines trends in technology and changes in the global structure of production, we also track the relationship between various aspects of job quality and involvement in GVCs (Fig. 2). Apart from the social environment and working time quality, the other dimensions of job quality tend to be negatively correlated with GVC intensity. In other words, some aspects of quality for European workers (such as skills and discretion, physical environment, and work intensity) may be worse in the sectors more heavily involved in globally fragmented value chains. Figs. 1-2 show simple unconditional correlation plots, which should serve as a starting point for a more in-depth econometric analysis of the determinants of multidimensional employee wellbeing, conditional upon specific worker or industry characteristics and involving the interplay between digital technologies and GVCs.

4. The relationship between digital technologies and working conditions: Econometric analysis

4.1. The models

To estimate the role of alternative factors in determining the working conditions of European workers, we employ econometric modelling techniques taking into account the multidimensional nature of the dependent variable (eq. 1) and mechanisms of impact in multiple dimensions (worker, occupation, sector/industry). Methodologically, we adopt a procedure akin to that of Baumgarten et al. (2013), Budría and Milgram Baleix (2020), Damiani et al. (2020) or Nikulin et al. (2022), based on merging labour market outcomes (here, working conditions), micro-level explanatory variables (features of individuals-workers), occupation, firm and sector-specific characteristics (productivity, digital technology, GVC intensity), as well as country groupings. The summary statistics of all the variables are presented in Table 5A in the Appendix.

To begin with, we estimate a regression model derived from the augmented Mincer earnings function (reviewed in Heckman et al., 2006), where GVCs and technology are treated separately. The relationship between digital technologies and working conditions is first assessed using the sectoral dimension (model 2a), then enriched with data on occupation-specific technological exposure (model 2b):

$$ln\left(WC_{ijsc}^{k}\right) = \alpha + \beta_1 Worker_i + \beta_2 Firm_j + \beta_3 lnProd_{sc} + \beta_4 GVC_{sc} + \beta_5 Tech_s + D_c + D_s + \varepsilon_{ijsc} \tag{2a}$$

$$ln\left(WC_{iojsc}^{k}\right) = \alpha + \beta_1 Worker_i + \beta_2 Firm_j + \beta_3 lnProd_{sc} + \beta_4 GVC_{sc} + \beta_5 Tech_o + D_c + D_s + \varepsilon_{iojsc}, \tag{2b}$$

where: i = worker, o = occupation, j = firm, s = sector of employment, c = country and k = the particular aspect of job quality captured in our working conditions measure (eq. 1). The log of the working conditions is regressed on: the vector of individual characteristics (*Worker)*, namely, sex, age, education, type of employment (a binary variable, full-time/part-time); firm-related characteristics (*Firm*: length of service in the enterprise, form of economic and financial control: public/private); industry productivity (*lnProd*: the log of the ratio of value added to total hours worked)[13]; and, finally, our main variable of interest: *Tech.* Dependence on digital technologies is measured either at sector level (eq. 2a) or occupation level (eq. 2b). Specifically, in eq. (2a) $Tech_s = \{Tech^{LDIU}, Tech^{MDIU}, Tech^{DP}\}$ follows the taxonomy of Van Ark et al., 2019 (Table 3A), while in eq. (2b) $Tech_o = \{Tech^{software}, Tech^{robot}, Tech^{AI}\}$ is captured via the degree of exposure to software, robots or AI (Webb, 2020). To address the remaining omitted-variables bias and to control for the multidimensional structure of the dataset, we include country and sector fixed effects: D_c gauges all country-specific characteristics, such as labour market regulation,[14] while D_s captures the remaining characteristics of sectors. The potential endogeneity problem is addressed in the robustness checks.

In models (2a) and (2b), *GVC* (i.e., FVA/exports - Wang et al., 2013) is included to check whether working conditions tend to be better or worse for workers in sectors more heavily involved in global production fragmentation (Nikulin et al., 2022). However, considering that technological progress and the topography of GVCs are intertwined (Baldwin, 2012, 2016; Baldwin and Venables, 2013), we augment the basic models with interactions between *GVC* and *Tech* – measured at sectoral or occupational level (eq. 3a and eq. 3b respectively):

$$ln\left(WC_{ijsc}^{k}\right) = \alpha + \beta_1 Worker_i + \beta_2 Firm_j + \beta_3 lnProd_{sc} + \beta_4 GVC_{sc} + \beta_5 Tech_s + \beta_6 GVC_{sc} \times Tech_s + D_c + D_s + \varepsilon_{ijsc} \tag{3a}$$

$$ln\left(WC_{iojsc}^{k}\right) = \alpha + \beta_1 Worker_i + \beta_2 Firm_j + \beta_{ln3} Prod_{sc} + \beta_4 GVC_{sc} + \beta_5 Tech_o + \beta_6 GVC_{sc} \times Tech_o + D_c + D_s + \varepsilon_{iojsc} \tag{3b}$$

The marginal effect of digital technology exposure on working conditions is equal to $\frac{\delta WC}{\delta Tech_s} = \beta_5 + \beta_6 GVC$ in eq. (3a) and $\frac{\delta WC}{\delta Tech_o} = \beta_5 + \beta_6 GVC$ in eq. (3b). The interactions help to determine whether the relationship between digital technologies and *WC* is moderated (or strengthened) by the intensity of GVC involvement.[15]

4.2. The estimation results

Our reading of the results begins with digital technology at the sectoral level. Table 1 presents the results of separate estimations for six different aspects of job quality, captured in our composite measure of working conditions. For the sake of clarity, here we present only the key variables – *Tech* and *GVC* – but all the models incorporate the other control variables (as indicated in eq. 2a; the complete results are reported in Table S3 in the Supplementary materials).[16] By sector, we find that working conditions are worse in sectors marked by intensive use of digital technology, designated MDIU (more digital-intensive use, as against LDIU, less digital-intensive use, the model's default/missing category). This result holds for all aspects of employee wellbeing. However, the sectors where digital technologies are actually produced (category DP – digital-producing) are different: in them, such aspects of

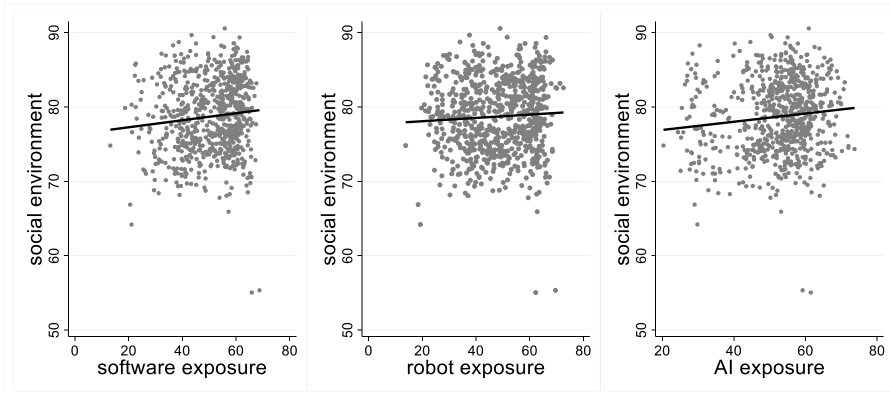
[13] Firm-level productivity is not provided in the original datasets.

[14] The Supplementary materials provide robustness check estimates, augmenting the model by specific country-level variables on labour market conditions (from ICTWSS) and trade openness (from Penn World Table).

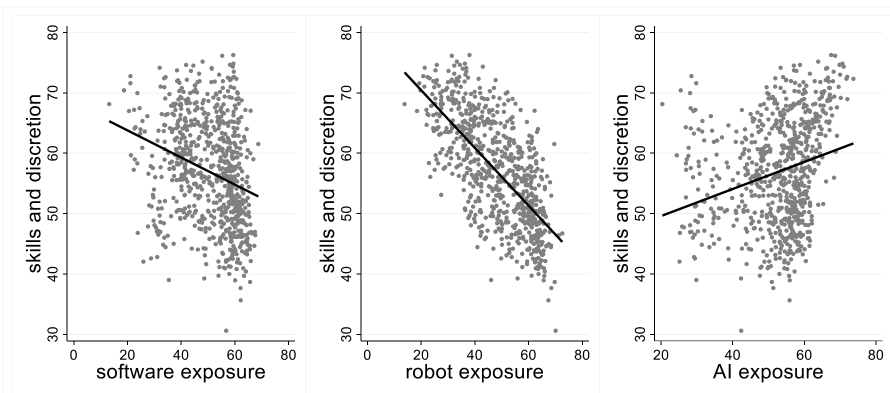
[15] Models (2a, 2b) and (3a, 3b) are estimated using weighted regression with robust standard errors clustered at the firm level. The weights are based on the rescaled SES grossing-up factor adjusted for the number of observations per country (so each country is equally represented in the sample). Additionally, we employ sector and country fixed effects. Alternatively, we could use a multilevel model, but it is based on strong assumptions (e.g. random allocation of individuals to higher level units) and is not recommended in country-comparative analysis (see Allison, 2009; Hox, 2010; Hazlett and Wainstein, 2022). On the basis of a simulation analysis, Maas and Hox (2005) conclude that only samples with more than 50 macro units produce unbiased multilevel estimators. Consequently, we stick to fixed effects model with clustered standard errors.

[16] Ceteris paribus, male, older, better educated, full-time workers, with permanent contracts and longer tenure in the enterprise enjoy better working conditions. Given that monetary wage is a component of the dependent variable, these results are in line with the Mincerian theory of wage determination (reviewed in Heckman et al., 2006).

A. social environment



B. skill and discretion



C. physical environment

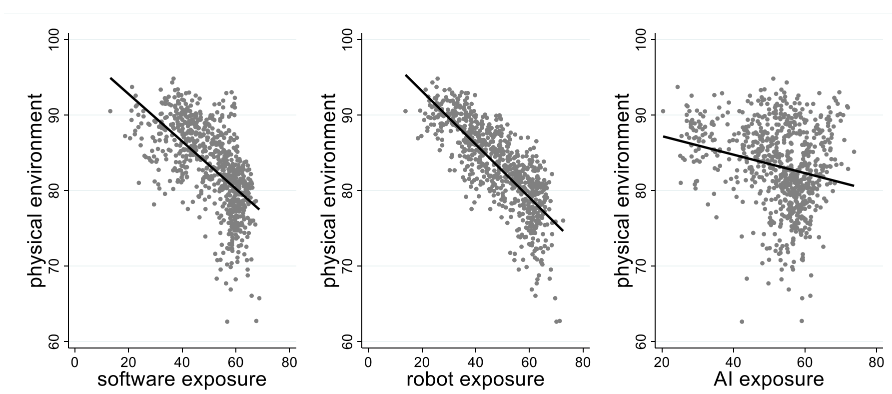
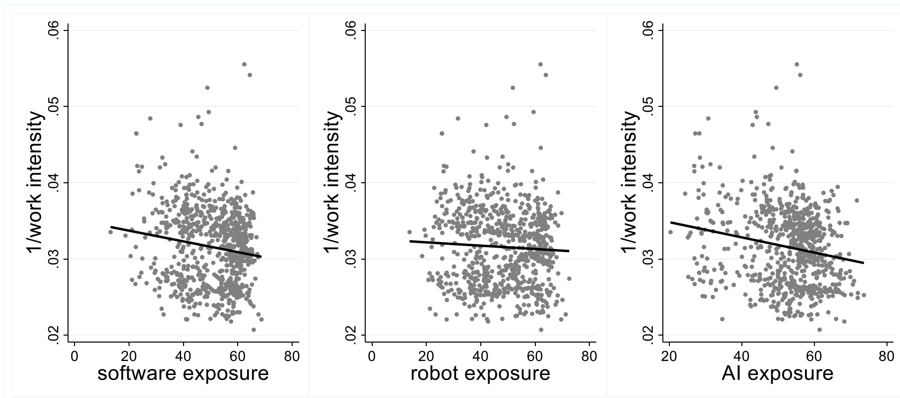
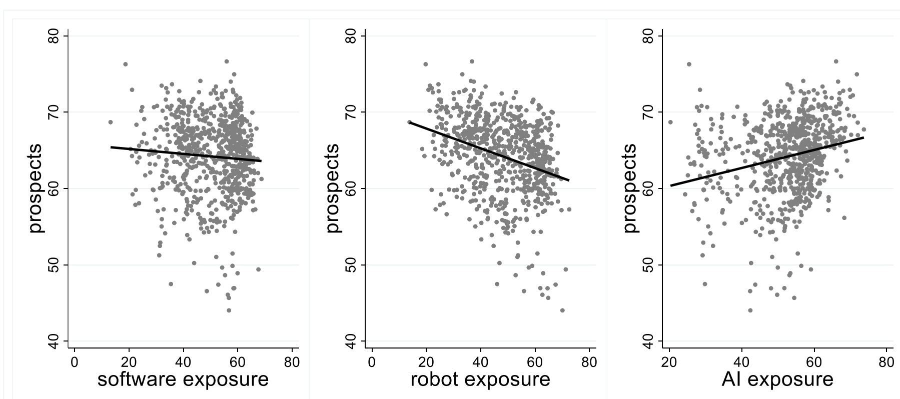


Fig. 1. Relationship between non-wage aspects of job quality and technological job content in Europe
A. social environment
B. skill and discretion
C. physical environment
D. work intensity
E. prospects
F. working time quality
Notes: Figures based on a sample of more than 9 millions of workers from 22 European countries. Dots correspond to country-industry weighted average across countries and sectors, with weights based on grossing-up factor for employees (from SES). To facilitate interpretation, we use the inverse of the original work intensity index.
Source: own elaboration based on job quality indices from EWCS (2015) merged with SES (2014) and technological exposure indicators (robot, software and AI specific) from Webb (2020).

D. work intensity



E. prospects



F. working time quality

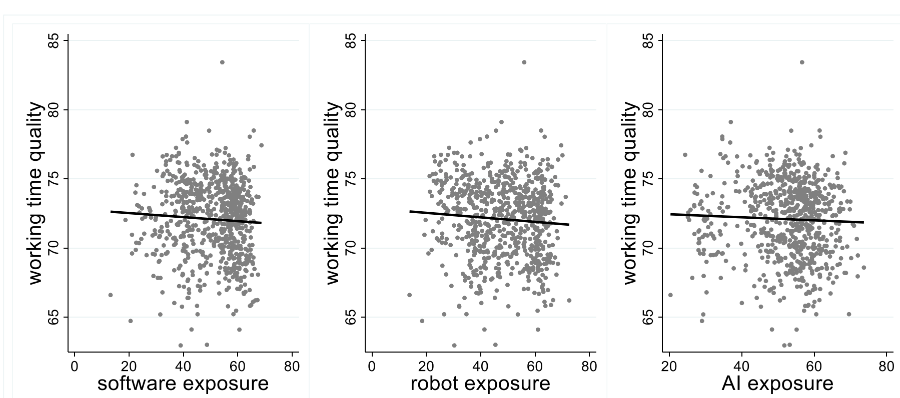


Fig. 1. (*continued*).

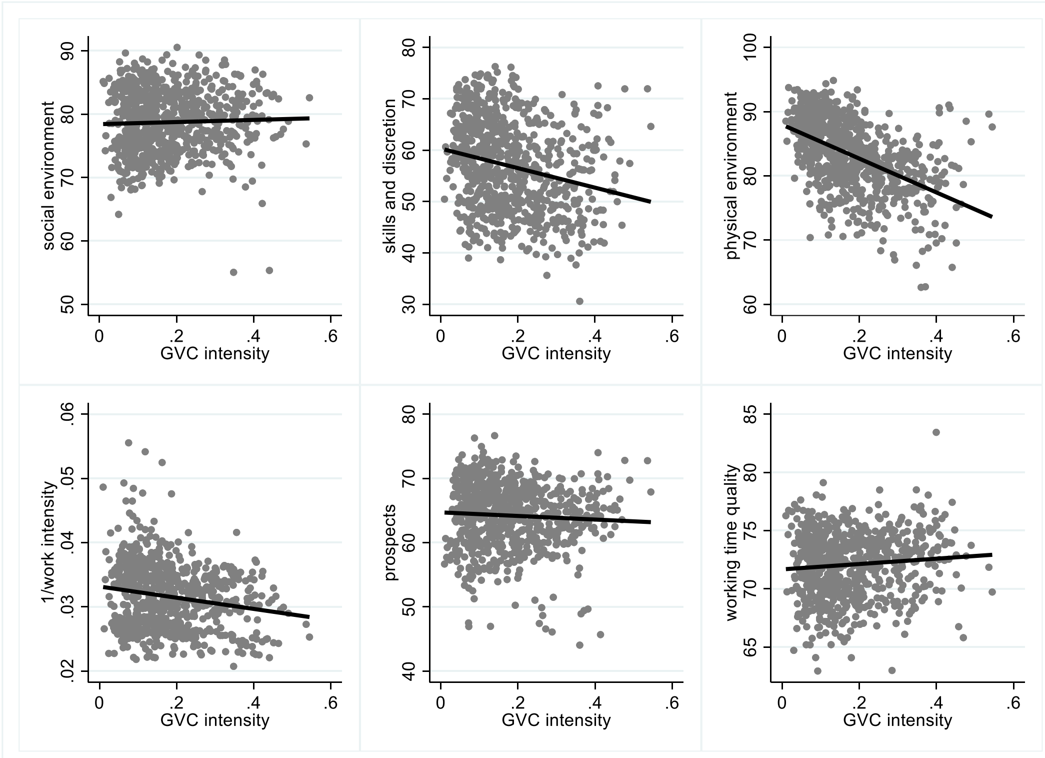


Fig. 2. Relationship between non-wage aspects of job quality and intensity of GVC involvement in Europe
Note: Figures based on a sample of more than over 9 million workers from 22 European countries. Dots correspond to country-industry weighted average across countries and sectors, with weights based on the grossing-up factor for employees (from SES). To facilitate interpretation, the inverse of the original work intensity index is used. GVC intensity measured in terms of sectoral share of foreign value added in gross exports.
Source: own elaboration based on job-quality indices from EWCS (2015) merged with SES (2014) and WIOD (2021).

Table 1
Estimation results – the link between sector digitalisation and working conditions.

	Working conditions (WC) capturing:					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
	(1)	(2)	(3)	(4)	(5)	(6)
GVC	−0.07	−0.182***	−0.119***	−0.173***	−0.155***	−0.156***
	[0.046]	[0.052]	[0.046]	[0.045]	[0.048]	[0.044]
$Tech_s^{MDIU}$	−0.325***	−0.209***	−0.230***	−0.240***	−0.298***	−0.319***
	[0.026]	[0.028]	[0.026]	[0.027]	[0.027]	[0.026]
$Tech_s^{DP}$	−0.018	0.199***	0.096***	0.027**	0.043*	0.004
	[0.028]	[0.031]	[0.029]	[0.029]	[0.029]	[0.028]
R2	0.79	0.75	0.79	0.78	0.78	0.8
N	9,214,247	9,218,140	9,218,140	9,216,546	9,218,140	9,218,140

Notes: Estimations based on a sample of workers from 22 European countries. Personal, firm and sectoral variables included in all specifications –full results reporting all RHS variables in Table S3 in Supplementary materials. Industry technological classification (Van Ark et al., 2019 – Table 3A): MDIU - most digital intensive-using sectors, DP - Digital Producing, the default/missing: category: LDIU - Least digital intensive using. Country and sector fixed effects included. Normalized weighted regression with robust standard errors clustered at the firm level (in parentheses), the weights are based on the rescaled grossing-up factor for employees (from SES) normalized by the number of observations per country.
Source: own calculation based on data from EWCS (2015), SES (2014) and WIOD (2021). *, **, and *** refer to 10%, 5%, and 1% level of significance, respectively.

job quality as skills and discretion or physical environment are better than in LDIU. This result suggests an interesting initial conclusion: namely that the wellbeing of workers in sectors using digital technologies differs from that of those in the sectors that produce them.

Additionally, we find that *GVC* involvement is negatively correlated with almost all aspects of working conditions (apart from social environment) - Table 1. To check how this result interacts with technology exposure, we can consider the results for the interaction between $Tech_s$ and *GVC* (Table 2 and Table S4 with a full set of covariates). Fig. 3 illustrates the main results: predicted working conditions (adjusted by the six job quality indices) are plotted against $Tech_s$ at three levels of GVC intensity: low, medium and high[17] according to sectors' foreign value

[17] High level of GVC corresponds to sectors with high (above 50 %) FVA share in exports such as: manufacture of motor vehicles, trailers and semi-trailers in Belgium and Slovakia; manufacture of computer, electronic and optical products in Slovakia or financial service activities in Luxembourg and Malta. For comparison, service sectors requiring personal interactions such as human health and social work activities, retail trade or education are characterised by low GVC involvement levels, with FVA share in exports not exceeding 5 % [source: WIOD, data for 2014].

added (FVA) share in exports (Koopman et al., 2014; Wang et al., 2013; Timmer et al., 2015; Shen and Silva, 2018; Parteka and Wolszczak-Derlacz, 2019). Fig. 3 should be interpreted as follows: the vertical position of each line reflects the general level of a specific working condition; for example, at low GVC intensity the best working conditions (no matter which job quality aspect is considered) are in DP and the worst in MDIU sectors. Generally, working conditions tend to worsen along with increasing participation in GVCs in the DP sectors. In both types of digital using sectors (MDIU, LDIU), however, working conditions do not change greatly with GVC intensification.

More precise conclusions can be drawn when technology is considered at the level of occupations (eq. 2b and 3b). Our key results refer to $Tech_o$ estimates, controlling for all the other worker and firm characteristics (full set of results in Tables S5–S7). There is a statistically significant negative correlation between working conditions and technology for the occupations most exposed to software and robots (note the coefficients obtained for $Tech_o$). At the same time, working conditions tend to be better in more AI-exposed occupations (i.e., when $Tech_o$ is measured via AI exposure - Table 3, panel C). As in the previous estimates, employees in the more GVC-intensive sectors tend to face worse working conditions (negative β_5 coefficient for the GVC variable).

Can we say that GVC acts as factor changing the technology-working conditions relationship? In other words, does the relationship between technological exposure of occupations and working conditions depend on the involvement in global production sharing? We obtain statistically significant estimates of β_6 of the augmented model, with interactions (results reported in Table 4, illustrated in Figs. 4A-4C), but are they significant in economic terms? To illustrate the magnitude of this effect, we again divide sectors into the three categories (low, medium and high GVC). Then we plot the predicted working conditions for these three levels of GVC against occupational technological exposure, considering our three types of technology – software (Fig. 4: panel 4A), robots (panel 4B), AI (panel 4C). At low levels of software exposure working conditions referring to social environment, work intensity, prospects and working time quality are worse in sectors with high GVC involvement, i.e. when more than half of exports depend on foreign value added. As software exposure increases, working conditions worsen in all aspects (negatively inclined lines) and, importantly, this change is similar at all GVC levels. More severe deterioration takes place at low and medium intense GVC levels only in such aspects as prospects and working time quality. Moreover, there is no significant difference in the general negative relationship between robot exposure and working conditions across different levels of GVC involvement (Fig. 4B). Overall, the interaction between technological factors related to robotisation or software, and GVC forces is weak.

Another pattern is observed in AI exposed jobs (Fig. 4C). We find that workers who are more exposed to AI enjoy better working conditions – this result is in line with the literature on the impact of the latest digital technologies on labour markets, underlying the specificity of AI with respect to previous waves of automation: for instance Felten et al. (2019) actually find that AI-exposed occupations experience a positive, if minor, change in wages. However, again, we find that the relationship between AI exposure and working conditions does not change significantly with increasing involvement in GVC. The variation observed in occupations weakly exposed to AI tends to vanish (as AI exposure increases) only in such aspects as work intensity, physical environment and working time quality.

Overall, summarizing all the estimates, we can conclude that working conditions are related to digital technologies and also to GVC, but the interaction between these two forces is weak and, if any, observed only in selected aspects of worker's wellbeing.

4.3. Robustness checks and extensions

In order to check the sensitivity of our results, we run a number of robustness tests. First we use an alternative technological classification of sectors, applying the digital industry taxonomy of Van Ark et al. (2019), which divides sectors into: less ICT-intensive-using (LIIU), more ICT-intensive-using (MIIU) and ICT-producing (IP) ones. The estimations of eq. 2a and eq. 3a (Table S8 and Table S9 in the Supplementary materials) confirm the difference between sectors that use and produce digital technologies (better working conditions in the latter) and the link between technology and employee wellbeing.

Secondly, given that our study is based on data for workers in many European countries, we consider cross-national heterogeneity via country-level controls. We re-estimate all versions of the baseline model (see the results in the Supplementary materials, Tables S10-S24), including measures of labour market institutions from the ICTWSS[18] (Visser, 2019) referring to wage-setting coordination[19] (Tables S10-S13), multi-level bargaining (the higher the index, the more centralised the bargaining scheme: Tables S14-S17) and the employment protection legislation (*EPL*) index from OECD[20] representing the strictness of regulations on dismissals and the use of temporary contracts[21] (Table S18 and S19). Next, we consider the unemployment rate from Eurostat (Table S20) and the general degree of trade openness measured via the share of exports (or imports) in GDP from PWT (Feenstra et al., 2015), which also helps to verify if the GVC measures in the baseline models capture overall trade integration (Tables S21-S24). Augmenting the regression by variables accounting for country-specific wage-setting mechanisms or openness does not alter the baseline results.

Next, to confirm the robustness of the results on the role of production-sharing intensity, we alter the way in which it is measured. That is, we replace our benchmark GVC measure (FVA/exports) with a traditional offshoring index, *OFF* (the ratio of imported intermediates to total sectoral output, Feenstra and Hanson, 1999) or with the global import intensity of production (*GII*) defined by Timmer et al. (2016) and used in Szymczak et al. (2022) who describe the procedure for calculating *GII*: it is based on the ratio of the sum of all intermediate imports along the entire chain for the final product (not only for the immediately preceding stage, as in *OFF*), divided by the value of the final product. Our main results for GVCs hold: greater involvement in global structures of production correlates negatively with working conditions (see Tables S25-S32). We find only a minor change in the statistical significance of the second-best production-sharing variables.

Additionally, we enrich our findings by checking the effects by the gender or age/life stage of workers. Tables S33 – S36 (in the Supplementary materials) report the results of model 2a (see the benchmark results in Table 1), but this time the regression is run separately for male and female workers. Similarly, estimates reported in Tables S37 – S42 split the sample according to the age classes: young (below 30 years old), average (30–49) and old (50 and above). The link between technological exposure and working conditions does not vary significantly across different age groups and is similar to the baseline result obtained for the whole population. On the other hand, higher participation in global production is associated with worse working conditions of female and young workers (negative and statistically significant coefficients ahead of GVC). A gender-biased GVC effect is in line with the results of Nikulin and Wolszczak-Derlacz (2022) who show that GVCs bring a higher

[18] ICTWSS - Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts.

[19] We take into account the recoded variable of the coordination of wage-setting (*Coord*) where 1 denotes centralised or industry-level bargaining (BE, DE, ES, IT, LU, NL, NO, SE) while 0 is for the countries with mixed industry and firm-level bargaining (BG, CY, CZ, EE, FR, HU, LT, LV, MT, PL, PR, RO, SK, UK).

[20] Available on https://www.oecd.org/employment/emp/oecdindicatorsofemploymentprotection.htm (accessed on 05.10.2023)

[21] EPL indexes describe regulations on the hiring and dismissal of employees, providing information on the level of job security for employees (related with the risk of being dismissed) and firm adaptability (the response to changing demand).

Table 2
Estimation results - the link between sector digitalisation and working conditions, conditional upon GVC involvement (interaction term).

	Working conditions (WC)capturing:					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
	(1)	(2)	(3)	(4)	(5)	(6)
GVC	−0.087	−0.211**	−0.232***	−0.098	−0.203***	−0.120*
	[0.073]	[0.086]	[0.071]	[0.068]	[0.077]	[0.070]
$Tech_s^{MDIU}$	−0.333***	−0.224***	−0.255***	−0.232***	−0.312***	−0.318***
	[0.028]	[0.030]	[0.028]	[0.029]	[0.029]	[0.028]
$Tech_s^{DP}$	0.02	0.266***	0.126***	0.071**	0.083***	0.048
	[0.031]	[0.033]	[0.031]	[0.032]	[0.032]	[0.031]
$Tech_s^{MDIU} \times GVC$	0.069	0.12	0.194***	−0.055	0.115	−0.001
	[0.077]	[0.089]	[0.074]	[0.073]	[0.078]	[0.073]
$Tech_s^{DP} \times GVC$	−0.253***	−0.444***	−0.172*	−0.315***	−0.260***	−0.306***
	[0.093]	[0.105]	[0.091]	[0.087]	[0.094]	[0.089]
R2	0.79	0.75	0.79	0.78	0.78	0.8
N	9,214,247	9,218,140	9,218,140	9,216,546	9,218,140	9,218,140

Notes: Estimations based on a sample of workers from 22 European countries. Personal, firm and sectoral control variables included – not reported (see full results in Table S4 in Supplementary materials). Sector digitalisation class according to Van Ark et al., 2019 (Table 3A): LDIU - Least digital intensive using, MDIU - most digital intensive-using, DP - Digital Producing. The default category is: LDIU: Least digital intensive using sectors. Country and sector fixed effects included. Normalized weighted regression with robust standard errors clustered at the firm level (in parentheses), the weights are based on the rescaled grossing-up factor for employees (from SES) normalized by the number of observations per country. *, **, and *** refer to 10%, 5%, and 1% level of significance, respectively.

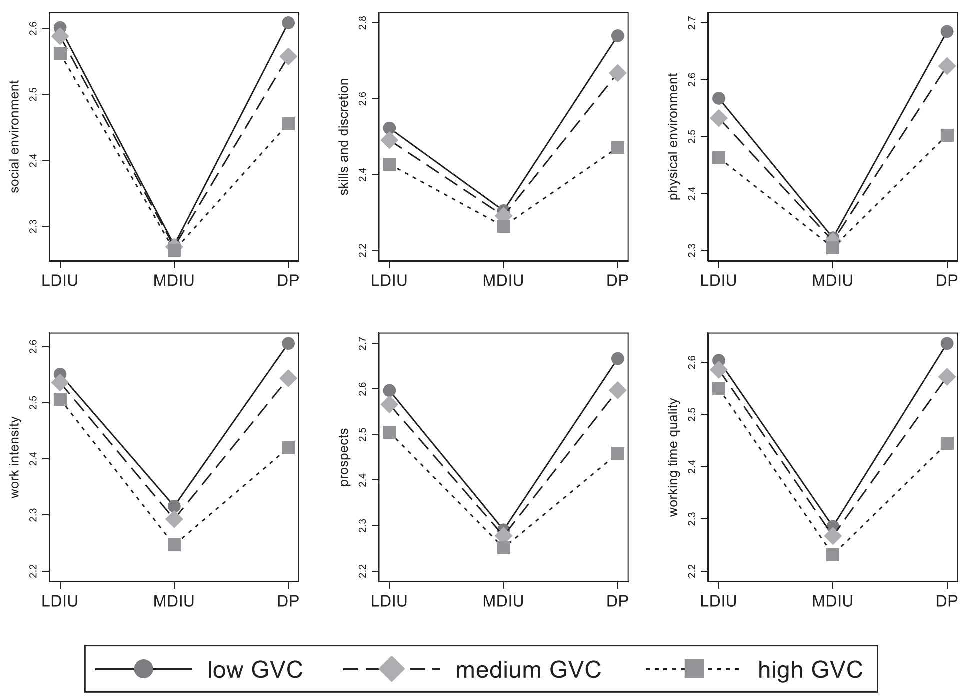


Fig. 3. Predicted working conditions over sector digitalisation level, by GVC intensity (illustrating the results from Table 2)
Notes: The lines on the figure correspond to GVC intensity, low GVC = 0.05; medium GVC = 0.2, high GVC = 0.5 (based on the distribution of GVC). Sector digitalisation class according to Van Ark et al., 2019 (Table 3A): LDIU - Least digital intensive using, MDIU - most digital intensive-using, DP - Digital Producing. Source: own elaboration based on job-quality indices from EWCS (2015) merged with SES (2014), WIOD (2021) and technological exposure indicators as proposed by Webb (2020).

gender wage gap, therefore females can be particularly affected by cross-border production fragmentation.

Finally, even though the two-way relationship between working conditions observed at the level of individuals and GVC involvement measured at the level of entire sectors is rather unlikely (so the problem of endogeneity should be limited), we run additional instrumental variable (IV) estimations where GVC participation is instrumented by observations on non-neighboring countries (an IV approach inspired by Autor et al., 2013). The IV results (see Tables S43 and S44) are similar to our baseline estimations and the main conclusions hold.

5. Conclusions

The dynamic development of digital technologies, combined with changes in the structure of production and its international fragmentation, are affecting the lives of workers worldwide. Our analysis focuses on an issue that has been relatively little studied in the socio-economic literature: working conditions captured via aspects other than wages. In particular, we have examined the intertwined associations between various digital technologies (ICT, robots, and also more recent AI solutions) and cross-border production links on employee wellbeing. We deem to provide several implications relevant for theory, research and

Table 3
Estimation results- the link between digital job content and working conditions.

Working conditions (WC) capturing:	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: software exposure						
GVC	−0.063	−0.167***	−0.105**	−0.166***	−0.146***	−0.148***
	[0.046]	[0.053]	[0.046]	[0.046]	[0.049]	[0.044]
$Tech_o^{software}$	−0.002***	−0.004***	−0.004***	−0.002***	−0.002***	−0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R2	0.79	0.75	0.79	0.79	0.78	0.8
N	9,214,247	9,218,140	9,218,140	9,216,546	9,218,140	9,218,140
Panel B: robot exposure						
GVC	−0.079*	−0.201***	−0.132***	−0.180***	−0.167***	−0.165***
	[0.045]	[0.047]	[0.043]	[0.045]	[0.046]	[0.042]
$Tech_o^{robot}$	−0.007***	−0.014***	−0.009***	−0.005***	−0.009***	−0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R2	0.81	0.81	0.82	0.79	0.81	0.82
N	9,214,247	9,218,140	9,218,140	9,216,546	9,218,140	9,218,140
Panel C: AI exposure						
GVC	−0.110**	−0.258***	−0.152***	−0.190***	−0.204***	−0.185***
	[0.046]	[0.050]	[0.045]	[0.045]	[0.047]	[0.043]
$Tech_o^{AI}$	0.005***	0.010***	0.004***	0.002***	0.006***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R^2	0.8	0.77	0.8	0.79	0.79	0.81
N	9,214,247	9,218,140	9,218,140	9,216,546	9,218,140	9,218,140

Note: Estimations based on a sample of workers from 22 European countries. Personal, firm and sectoral variables included in all specifications – detail results reporting all RHS variable in Tables S5 – S7 in Supplementary materials. Country and sector fixed effects included. Normalized weighted regression with robust standard errors clustered at the firm level (in parentheses).
Source: own calculation based on data from EWCS (2015), SES (2014) and WIOD (2021).

Table 4
Estimation results- the link between digital job content and working conditions, including interaction between *GVC* and $Tech_o$.

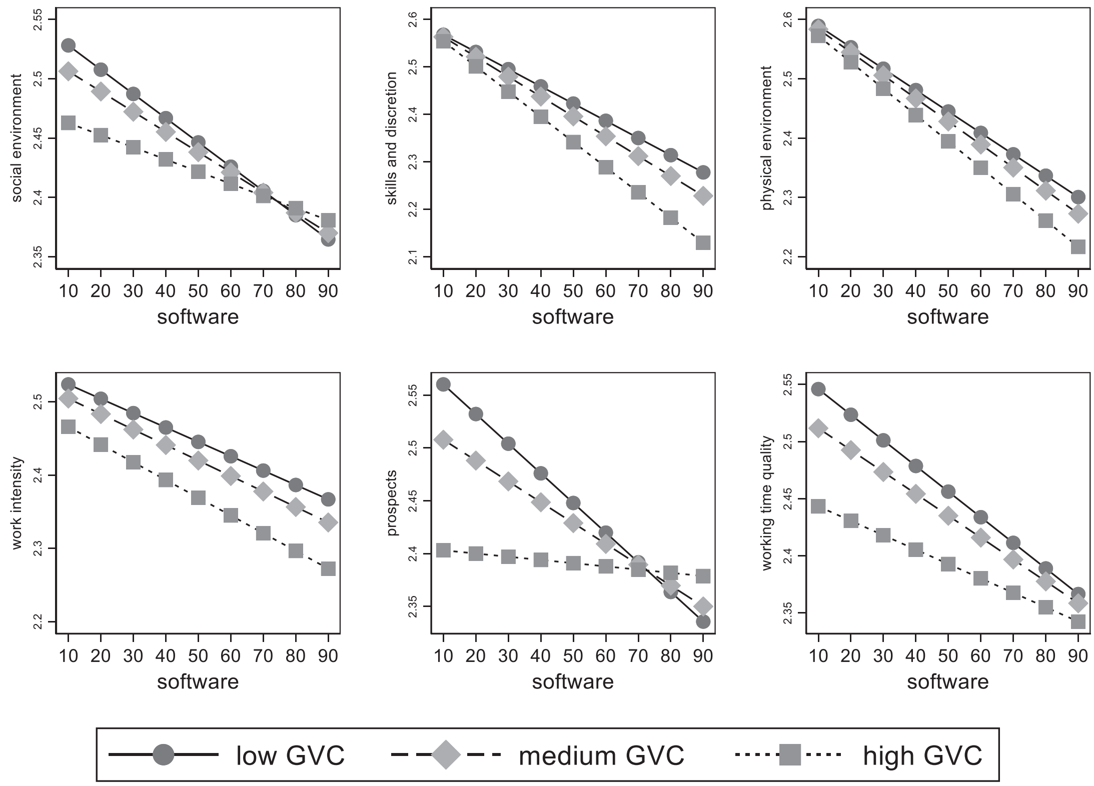
	Working conditions (WC) capturing:					
	Social environment	Skills and discretion	Physical environment	Work intensity	Prospects	Working time
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: software exposure						
GVC	−0.168***	0.007	−0.019	−0.118**	−0.404***	−0.250***
	[0.058]	[0.067]	[0.055]	[0.060]	[0.059]	[0.052]
$Tech_o^{software}$	−0.002***	−0.003***	−0.004***	−0.002***	−0.003***	−0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_o^{software} \times GVC$	0.002***	−0.004***	−0.002**	−0.001	0.006***	0.002***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
R2	0.79	0.75	0.79	0.79	0.78	0.8
N	9,214,247	9,218,140	9,218,140	9,216,546	9,218,140	9,218,140
Panel B: robot exposure						
GVC	−0.338***	−0.359***	−0.191***	−0.121**	−0.567***	−0.377***
	[0.049]	[0.053]	[0.048]	[0.053]	[0.050]	[0.046]
$Tech_o^{robot}$	−0.008***	−0.015***	−0.010***	−0.005***	−0.010***	−0.007***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_o^{robot} \times GVC$	0.006***	0.004***	0.001**	−0.001**	0.010***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
R2	0.81	0.81	0.82	0.79	0.81	0.82
N	9,214,247	9,218,140	9,218,140	9,216,546	9,218,140	9,218,140
Panel C: AI exposure						
GVC	−0.292***	−0.620***	−0.348***	−0.584***	−0.432***	−0.335***
	[0.056]	[0.065]	[0.054]	[0.060]	[0.058]	[0.052]
$Tech_o^{AI}$	0.005***	0.009***	0.004***	0.001***	0.006***	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$Tech_o^{AI} \times GVC$	0.004***	0.007***	0.004***	0.008***	0.004***	0.003***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
R^2	0.8	0.77	0.8	0.79	0.79	0.81
N	9,214,247	9,218,140	9,218,140	9,216,546	9,218,140	9,218,140

Note: Estimations based on a sample of workers from 22 European countries. Personal and firms characteristics included as in Table S5. Country and sector fixed effects included. Normalized weighted regression with robust standard errors clustered at the firm level (in parentheses).
Source: own calculation based on data from EWCS (2015), SES (2014) and WIOD (2021).

practice.

From the point of view of the theory, we confirm the importance of multidimensional frames for analysing employee wellbeing that interact with job demands and job resources (Bakker and Demerouti, 2007). Additionally, we relate to the frameworks that do not isolate the worker-level impact of technological progress from changes in business models owing to the intensification of global value chains (Baldwin, 2012, 2016; Antràs and Chor, 2022). Our results, are based on a set of augmented

Panel 4.A. Software exposure



Panel 4 B. Robot exposure

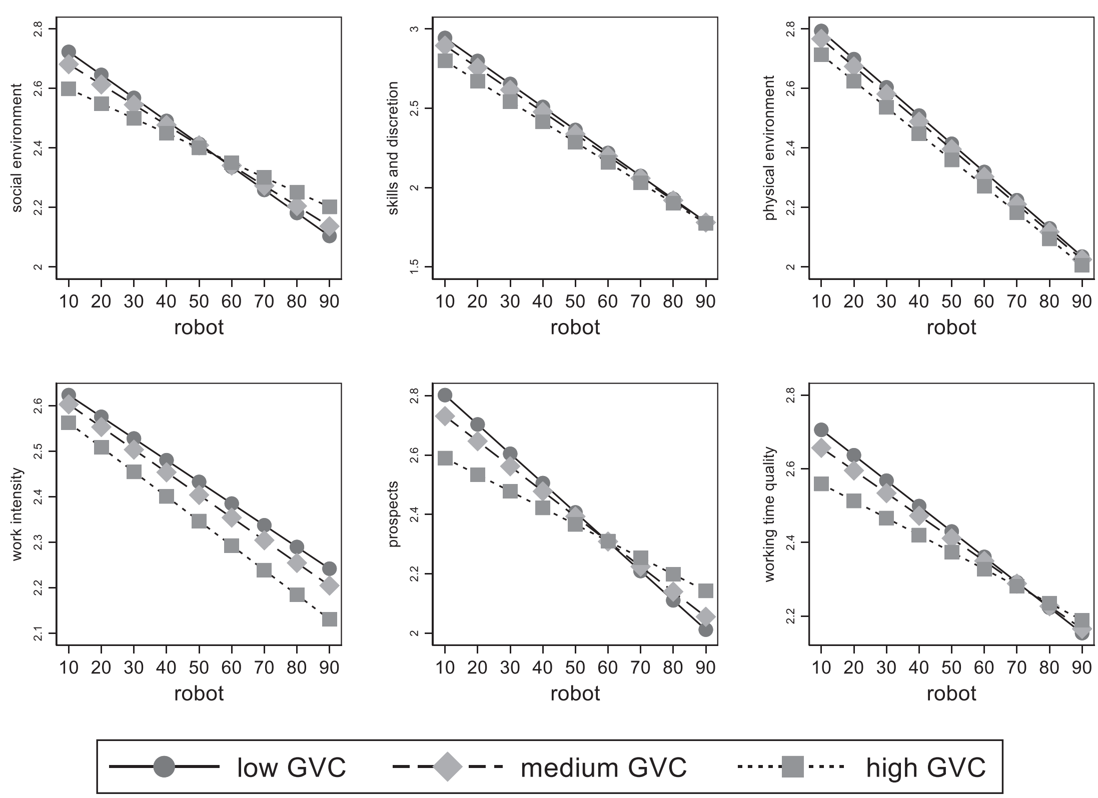


Fig. 4. Predicted working conditions at different GVC intensity over digital job content (illustrating the results from Table 4)
Panel 4.A. Software exposure
Panel 4 B. Robot exposure
Panel 4C. AI exposure
Note: The lines on each chart correspond to GVC intensity: low GVC = 0.05; medium GVC = 0.2, high GVC-0.5 (based on the distribution of GVC).
Source: own elaboration based on job-quality indices from EWCS (2015) merged with SES (2014), WIOD (2021) and technological exposure indicators by Webb (2020).

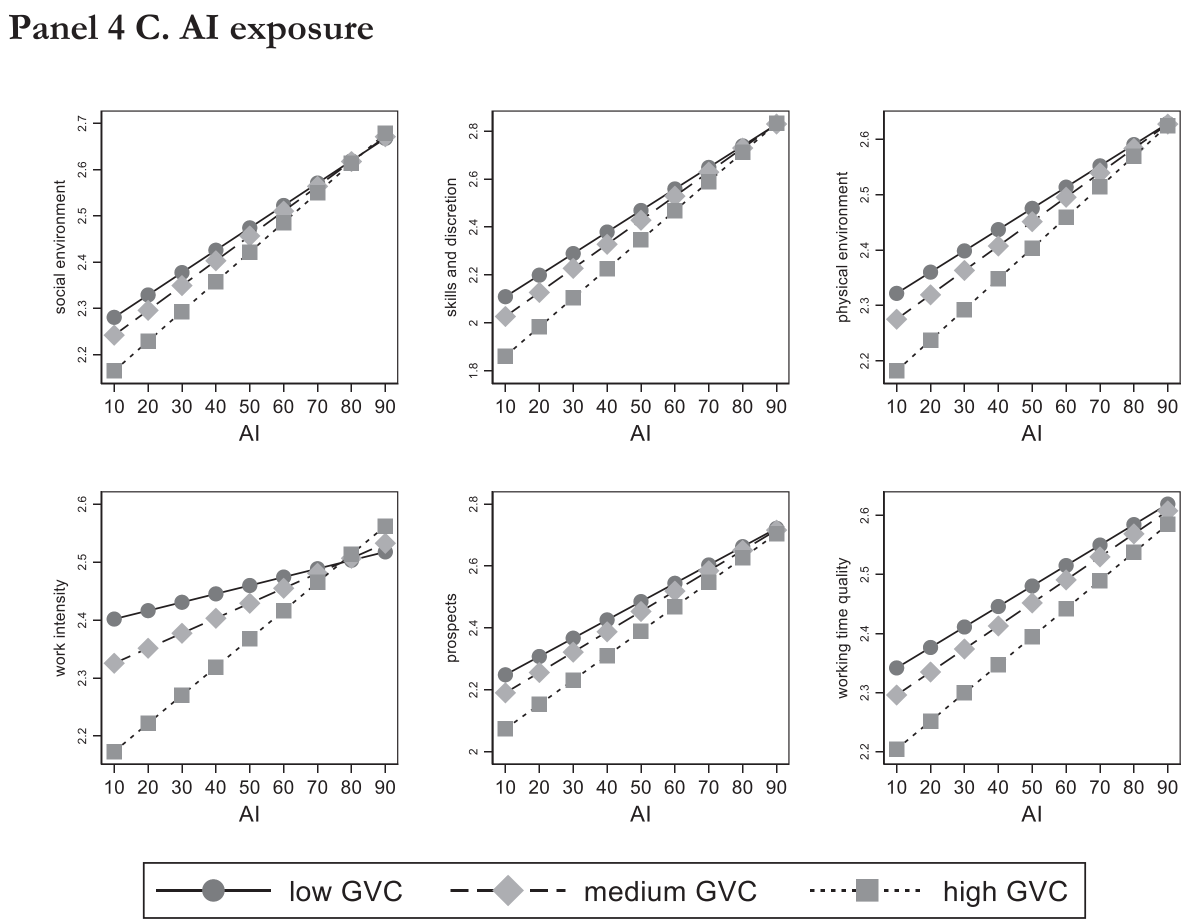


Fig. 4. (*continued*).

models for the determination of working conditions, interacting with technological and GVC forces. We find that even though GVC intensity correlates negatively with many aspects of working conditions, cross-border production fragmentation is a weak moderator of the core relationship between technology exposure and working conditions.

In terms of implications for research on the social consequences of technological change, our study has expanded the empirical frontier. For the purpose of this analysis we have constructed a rich dataset, merging worker-level information on socio-demographic characteristics, wages, and several non-income aspects of job quality, as well as GVC- and technology-related features. For a large sample (over 9 million workers in 22 European countries), we provide evidence that is neither country- nor industry-specific. At the same time, we capture individual-, occupation-, sector- and country-level heterogeneity with a wide array of control variables. As to working conditions, we have shown that the relevant factors go beyond pure monetary remuneration. Our holistic approach, rooted in the sociological literature, captures the physical and social environment at work, work intensity, working time quality, skills and discretion, and prospects.Moreover, we assess digitalisation at two levels: sectoral and occupational, at the same time analysing if technological developments interact with the pressure exerted by the fragmentation of production. Finally, while much of the literature to date has focused on the impact of ICT on workers, we provide evidence of interesting differences between AI, software or robot technology.

The practical implications of our study refer to policy and social challenges due to digital technological progress on one hand, and progressing value chain integration on the other. We find that employee wellbeing definitely differs between the industries that *use* digital technologies and those that *produce* them. What is more, we reveal that the way in which digital technology operates depends on the specific *type of* technology, thus targeted policy response and social protection is needed. Workers whose occupations are particularly exposed to software and robots are worse off, while in AI-exposed jobs they tend to improve. This finding is in line with the recent evidence that AI technologies are indeed unique – in particular, unlike software and robotics, AI is targeted towards high-skilled tasks (Brynjolfsson et al., 2018; Brynjolfsson and Mitchell, 2017; Webb, 2020; Lane and Saint-Martin, 2021).

Despite the multidimensional approach used in our analysis, we are aware of several limitations than need to be acknowledged. Firstly, the features of the source datasets used in our work do not allow us to account for within-occupational differences in job quality. This is a common problem and most of the related studies focus on differences in selected job quality aspects (mainly wages) between occupations (see the review by Stier and Yaish, 2014). However, intra-occupational wage inequalities have been reported for single countries, such as the US (Kim and Sakamoto, 2008) or the UK (Williams, 2013), so this limitation should be kept in mind while interpreting our results. Moreover, due to the cross-sectional nature of the microdata, we cannot monitor changes in employee wellbeing over time.

Further extensions of our analysis could involve the use of newer and more detailed measures. The EWCS indices based on surveys done in the Covid-19 era were released in late November 2022, once our study was already finished. In the future, new data could be used to investigate how the more intense use of digital technologies during the pandemic (owing to emergency-imposed remote work) affected employee well-being, in particular, in such areas as work-life balance, work intensity or satisfaction from the social and physical environment at work. Another possible avenue of research relates to gender differences in working conditions, and their technological determinants (the structure of employment in technology-intensive sectors and occupations tends to be gender-unequal). Finally, given the rapidly changing working relations (including on-demand job and platform work), an analysis by the type of employment contract could provide important additional insights.

Funding

Aleksandra Parteka was responsible for the research on technological specialisation, which was supported by the National Science Centre, Poland (grant number: 2020/37/B/HS4/01302). Joanna Wolszczak-Derlacz was responsible for the research on GVCs, which was supported by the National Science Centre, Poland (grant number: 2015/19/B/HS4/02884). Dagmara Nikulin was responsible for the research based on working conditions data. We are also grateful for the support of the European Trade Union Institute and the insightful comments of their members on the initial research results (ETUI WP 2022.12).

CRediT authorship contribution statement

All three authors contributed to the study conceptualisation and design.

Aleksandra Parteka: Conceptualization, Methodology, Resources, Formal analysis, Investigation, Validation, Writing – original draft, Writing – review & editing. **Joanna Wolszczak-Derlacz:** Conceptualization, Methodology, Resources, Formal analysis, Investigation, Validation, Writing – original draft. **Dagmara Nikulin:** Conceptualization, Methodology, Resources, Formal analysis, Investigation, Validation, Writing – original draft, Writing – review & editing.

Data availability

Data and codes will be made available on request (except for the data not publicly available). We need to specify this because microdata that we use cannot be dissaminated due to data protection policy by Eurostat (see footnote [7]).

Appendix A. Appendix

Table 1A
Summary of the literature on digital technology and working conditions/job quality.

Name of the author(s)	Country coverage	Sample, level of analysis/ methodology	Digital technology aspect (measure)	Working conditions aspect (measure)	Main results
(Badri et al., 2018)	Theoretical studies	Literature review of publications containing the words "health and safety" with the content of Industry 4.0 since 2012, recorded in the Scopus database; 11 publications were analysed	Six technological categories relevant to Industry 4.0: big data, internet of things, cyber-physical system, robotics, artificial intelligence, simulation	Four aspects of occupational health and safety: (1) organisation of work, (2) OHS legislative and regulatory framework, (3) OHS management systems and (4) management of occupational risks	Need for more interdisciplinary research to improve the integration of human labour with intelligent equipment
(Tarafdar et al., 2007)	US	Empirical survey data on 233 ICT users from two public sector organisations	ICT-induced stress (technostress) factors, based on a survey study	Role stress related to a lack of clarity regarding the scope of one's responsibilities in the organisation. The main factors of role stress are associated with role conflict and role overload at work	Different dimen- sions of technostress should be added to existing concepts on stress
(Salanova et al., 2014)		1072 ICT users covering two samples according to the intensity of ICT use. ICT use is defined as either as a basic tool at work or not a frequent tool at work	Technostress divided into technostrain (feelings of anxiety, fatigue, scepticism and inefficacy belief related to the use of technologies) and technoaddiction (bad feeling due to an excessive and compulsive use of these technologies)	Work overload, role ambiguity, emotional overload, mobbing, autonomy, transformational leadership, social support	Job demands are positively related to technostrain and technoaddiction, while job and personal resources are negatively related to technostrain and technoaddiction
(Berg-Beckhoff et al., 2017)	Norway, European Union, Asia, Korea, Hong Kong, China, USA, Canada, Brazil, New Zealand, Australia	Systematic literature review using PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines and based on the scientific databases: PubMed, Web of Science, Psycinfo, and the Cochrane Library. 29 cross-sectional studies were selected	ICT: the percentage of working time using ICT (mostly only connected to a computer), or the hours working with ICT	Stress and burnout	Significant association between ICT and burnout, mostly in the middle-aged working population

(continued on next page)

Table 1A (*continued*)

Name of the author(s)	Country coverage	Sample, level of analysis/ methodology	Digital technology aspect (measure)	Working conditions aspect (measure)	Main results
(Lane and Saint-Martin, 2021)	US	Literature review based on selected publications on the impact of AI on the reorganisation of work	Artificial Intelligence	Content and design of jobs	AI is likely to reshape the work environment
(Webb, 2020)	US	Regression analysis aimed at measuring the relationship between technology exposure scores and changes in employment and wages (US wages from 1980 to 2010)	Occupational exposure to robots, software and AI	Data on wages in a given occupation-industry	Low-skill occupations are most exposed to robots, middle-skill occupations are most exposed to software, high-skill occupations are most exposed to artificial intelligence
(Brynjolfsson et al., 2018)	US	2069 work activities, 18,156 tasks, and 964 occupations from the O*NET database combined with suitability for machine learning measures (based on a 21-question rubric for assessing the suitability of tasks for machine learning)	Suitability for machine learning (SML): the level to which machine learning may transform a job	Log median occupational wage	The correlation between SML and the median occupational wage is low
(Felten et al., 2019)	US	Regression analysis based on wage data from the Bureau of Labor Statistics (BLS) for each occupation from 2010 to 2016 and AI Occupational Impact constructed from the Electronic Frontier Foundation (EFF), AI Progress Measurement dataset and the Occupational Information Network (O*NET)	AI Occupational Impact (AIOI), which links specific applications of AI (image recognition, translation, ability to play strategic games) to workplace abilities and occupations	Wages on the occupational level	On average, occupations impacted by AI experience a small but positive change in wages, especially in occupations with higher software skill requirements and in higher-income occupations
(Antón et al., 2023)	80 NUTS-2 regions from 12 EU countries: Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Portugal, Spain, Sweden and the United Kingdom	Regression analysis aimed at exploring the impact of robot adoption on working conditions at the regional level	Regional variation in the increase in the adoption of robots (robot exposure) based on the World Robotics Survey data	Change in the average job quality indicator (related to work intensity, physical environment, skills and discretion) in a given region	Robotisation is negatively associated with work intensity; no relevant association with the physical environment or skills and discretion.
(Bhargava et al., 2021)	United Arab Emirates, Oman, India, the UK, the USA, and South Africa	21 semi-structured interviews with a diverse sample from consulting, accounting and finance, and hospitality industries	Working adults' perceptions of the implementation of robotics, artificial intelligence (AI), and automation	Working adults' perceptions on job security, job satisfaction, and employability	The "human touch" and "soft skills" cannot be replicated by automation processes; employees perceive automation as an opportunity; mixed association between automation processes and job satisfaction
(Turja et al., 2022)	Finland	Quality of Work Life Survey (QWLS) data collected in Finland in 2018 ($N = 4110$); OLS regression analysis aimed at finding an association between the level of robotisation in the workplace and work satisfaction	Earners working in a robotised workplace (three different levels: not working with robots firsthand, working with robots half or less than half of the working time, and working with robots most of the time)	Intrinsic job satisfaction and perceived meaningfulness of the jobs based on the survey results	Intrinsic job satisfaction at work is on average lower in robotised workplaces than in non-robotised workplaces
(Damiani et al., 2020)	Italy and Germany	Multi-level estimates of two countries (Italy and Germany), combining sectoral data on robot use with person-level data on properties of workers: Mincer-type wage equations on the impact of robot use on wages earned	Industry-level data from the International Federation of Robotics (IFR) for robot exposure	Worker-level data from the Structure of Earnings Survey (SES) from 2010 and 2014	A need for controlling for innovation regimes. Robot use has adverse effects on workers in 'high-cumulativeness' of knowledge industries as opposed to 'low-cumulativeness' industries.

Table 2A
The set of countries.

Country code	Country name	Country code	Country name
BE	Belgium	LU	Luxembourg
BG	Bulgaria	LV	Latvia
CY	Cyprus	MT	Malta
CZ	the Czech Republic	NL	the Netherlands
DE	Germany	NO	Norway
EE	Estonia	PL	Poland
ES	Spain	PT	Portugal
FR	France	RO	Romania
HU	Hungary	SE	Sweden
IT	Italy	SK	Slovakia
LT	Lithuania	UK	The United Kingdom

Table 3A
The list of sectors (industries) and their technological (digital) classification.

Industry code (NACE rev.2)	Digital industry taxonomy (Van Ark et al., 2019)	Industry code (NACE rev.2)	Digital industry taxonomy (Van Ark et al., 2019)
B	*LDIU*	*D35*	*LDIU*
C10-C12	*LDIU*	*E36*	*LDIU*
C10_C13	*LDIU*	*E36_E37-E39*	*LDIU*
C13-C15	*LDIU*	*E37-E39*	*LDIU*
C16_C17	*MDIU*	*F*	*LDIU*
C16_C17_C18	*MDIU*	*G45_G46*	*MDIU*
C18	*MDIU*	*G47*	*MDIU*
C19_C20_C21_C22	*LDIU*	*H49_H50_H51_H52*	*LDIU*
C19_C20_C21_C22_C23	*LDIU*	*H53*	*LDIU*
C19_C20_C22	*LDIU*	*I*	*LDIU*
C19_C20_C22_C23	*LDIU*	*J58_J59_J60*	*DP*
C21	*LDIU*	*J61_J62_J63*	*DP*
C21_C26_C27_C33	*DP*	*K64_K65_K66*	*MDIU*
C21_C29_C30	*MDIU*	*L68*	*LDIU*
C23	*LDIU*	*M69_M70*	*MDIU*
C24_C25	*LDIU*	*M69_M70_M71*	*MDIU*
C24_C25_C28	*LDIU*	*M71*	*MDIU*
C26_C27_C33	*DP*	*M72_M73_M74_M75*	*MDIU*
C28	*MDIU*	*M74_M75*	*MDIU*
C29_C30	*MDIU*	*N*	*MDIU*
C29_C30_C31_C32	*MDIU*	*O84*	*MDIU*
C31_C32	*MDIU*	*P85*	*LDIU*
		Q	*LDIU*
		R_S	*MDIU*

Note: DP = Digital Producing, LDIU = Least digital intensive using, MDIU = Most digital intensive-using sectors. In the case of grouped sectors we performed manual matching.
List of sectors according to WIOD: https://web.archive.org/web/20211102093643/https://www.rug.nl/ggdc/html_publications/memorandum/gd162.pdf p. 43.

Table 4A
Correlations between non-wage job quality indices and wages.

	Wage	Social environment	Skills and discretion	Physical environment	1/work intensity*	Prospects	Working time quality
Wage	1						
Social environment	−0,096	1					
Skills and discretion	0,438	0,119	1				
Physical environment	0,183	0,103	0,507	1			
1/work intensity*	−0,236	0,056	−0,225	0,218	1		
Prospects	0,275	0,163	0,641	0,332	−0,228	1	
Working time quality	−0,055	0,188	−0,090	0,146	0,220	−0,108	1

Note: sample: over 9 million workers from 22 European countries; *to facilitate interpretation, we use the inverse of original work intensity index. The calculations employ weights based on grossing-up factor for employees (from SES (2014)). The description of job quality indices is provided in Table S2 in Supplementary materials.
Source: own elaboration based on indices from EWCS (2015) and wage data from SES (2014).

Table 5A
Summary statistics of the variables used in the estimations.

	N	Mean	Std. Dev.	Min	Max
Job quality indices and working conditions					
EWCS original job quality indices					
Social environment	9,522,312	77.97	7.63	8.33	100.00
Skills and discretion	9,526,356	57.29	14.73	8.32	96.48
Physical environment	9,526,356	84.35	8.49	42.31	100.00
*Work intensity**	9,524,762	32.91	7.39	1.85	86.00
Prospects	9,526,356	64.28	7.80	25.00	100.00
Working time	9,526,356	71.55	5.51	30.33	87.90
Working conditions (in logs, as in eq. 1) capturing:					
Social environment	9,522,224	2.20	0.89	−0.81	4.59
Skills and discretion	9,526,268	1.87	1.05	−1.47	4.51
Physical environment	9,526,268	2.28	0.92	−0.23	4.71
*Work intensity***	9,524,674	−5.61	0.86	−8.41	−2.28
Prospects	9,526,268	2.01	0.94	−0.99	4.47
Working time	9,526,268	2.12	0.90	−0.19	4.50
Technology exposure					
Software exposure	9,526,356	45.11	20.05	6.00	87.00
Robot exposure	9,526,356	44.83	23.78	10.00	86.00
AI exposure	9,526,356	47.67	19.93	11.00	90.00
Individual, job and firm characteristics					
Sex	9,526,356	0.50	0.50	0.00	1.00
Ageyoung	9,526,356	0.17	0.38	0.00	1.00
Ageaverage	9,526,356	0.52	0.50	0.00	1.00
Ageold	9,526,356	0.31	0.46	0.00	1.00
Loweduc	9,526,356	0.16	0.37	0.00	1.00
Mededuc	9,526,356	0.45	0.50	0.00	1.00
Higheduc	9,526,356	0.39	0.49	0.00	1.00
FT	9,526,356	0.82	0.39	0.00	1.00
Shortdur	9,526,356	0.13	0.34	0.00	1.00
Meddur	9,526,356	0.30	0.46	0.00	1.00
Longdur	9,526,356	0.37	0.48	0.00	1.00
Vlongdur	9,526,356	0.20	0.40	0.00	1.00
Public	9,242,482	0.37	0.48	0.00	1.00
GVC measures					
FVA/Export	9,502,091	0.15	0.10	0.01	0.54
OFF	9,526,356	0.13	0.12	0.00	0.69
GII	9,526,356	0.28	0.20	0.00	0.99

Note: Weighted statistics, the weights are based on the rescaled grossing-up factor for employees (from SES) normalized by the number of observations per country.
Source: own elaboration based on indices of job quality from EWCS (2015) merged with SES (2014),technological exposure indicators from Webb (2020) and sectoral data from WIOD (2016).

* Original EWCS job quality index: higher working intensity implies lower job quality.

** Working conditions based on the inverse of work intensity job quality index.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2023.122998.

References

Acemoglu, D., Autor, D.H., 2011. Skills, tasks and technologies: Implications for employment and earnings. In: Ashenfelter, O., Card, D.E. (Eds.), Handbook of Labor Economics, vol. 4B. Elsevier, Amsterdam, pp. 1043–1171.

Acemoglu, D., Restrepo, P., 2018. The race between man and machine: implications of technology for growth, factor shares, and employment. Am. Econ. Rev. 108 (6), 1488–1542.

Acemoglu, D., Restrepo, P., 2019. Automation and new tasks: how technology displaces and reinstates labor. J. Econ. Perspect. 33 (2), 3–30.

Acemoglu, D., Restrepo, P., 2020. Robots and jobs: Evidence from US labor markets. J. Polit. Econ. 128 (6).

Aghion, P., Jones, B.F., Jones, C.I., 2019. Artificial intelligence and economic growth. In: Agrawal, Gans, Goldfarb (Eds.), *The Economics of Artificial Intelligence: An Agenda*, pp. 237–290.

Agrawal, A., Gans, J., Goldfarb, A. (Eds.), 2019. The Economics of artificial intelligence: An Agenda. University of Chicago Press, Chicago.

Allison, P.D., 2009. Fixed effects regression models. SAGE Publications.

Amador, J., Cabral, S., 2015. Global value chains, labour markets and productivity. In: Amador, J., di Mauro, F. (Eds.), The Age of Global Value Chains, Maps and Policy Issues. CEPR Press, London, pp. 107–120.

Antón, J.I., Fernández-Macías, E., Winter-Ebmer, R., 2023. Does robotization affect job quality? Evidence from European regional labor markets. Industrial Relations: A Journal of Economy and Society 62 (3), 233–256.

Antràs, P., Chor, D., 2022. Global value chains. Handb. Int. Econ. 5, 297–376.

Autor, D., Handel, M., 2013. Putting tasks to the test: human capital, job tasks, and wages. J. Labor Econ. 31 (2), 59–96.

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 (5), 1553–1597.

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.

Autor, D.H., Dorn, D., Hanson, G.H., 2013. The China syndrome: local labor market effects of import competition in the United States. Am. Econ. Rev. 103 (6), 2121–2168.

Autor, D.H., Dorn, D., Hanson, G.H., Song, J., 2014. Trade adjustment: Worker-level evidence. Q. J. Econ. 129 (4), 1799–1860.

Autor, D.H., Dorn, D., Hanson, G.H., 2015. Untangling trade and technology: evidence from local labour markets. Econ. J. 125 (584), 621–646.

Badri, A., Boudreau-Trudel, B., Souissi, A.S., 2018. Occupational health and safety in the industry 4.0 era: a cause for major concern? Saf. Sci. 109, 403–411.

Bakker, A.B., Demerouti, E., 2007. The job demands-resources model: state of the art. J. Manag. Psychol. 22 (3), 309–328.

Baldwin, R., 2012. Global Supply Chains: Why they Emerged, why they Matter, and where they Are Going. CEPR Discussion Papers, p. 9103.

Baldwin, R., 2016. The Great Convergence. Information Technology and the New Globalization. Harvard University Press.

Baldwin, R., Venables, A.J., 2013. Spiders and snakes: offshoring and agglomeration in the global economy. J. Int. Econ. 90 (2), 245–254.

Baruffaldi, S., et al., 2020. Identifying and measuring developments in artificial intelligence: Making the impossible possible. In: OECD Science, Technology and Industry Working Papers, No. 2020/05. OECD Publishing, Paris. https://doi.org/10.1787/5f65ff7e-en.

Basco, S., Mestieri, M., 2018. Mergers along the global supply chain: information technologies and routine tasks. Oxf. Bull. Econ. Stat. 80 (2), 406–433.
Baumgarten, D., Geishecker, I., Görg, H., 2013. Offshoring, tasks and the skill-wage pattern. Eur. Econ. Rev. 61, 132–152.
Berg-Beckhoff, G., Nielsen, G., Ladekjær Larsen, E., 2017. Use of information communication technology and stress, burnout, and mental health in older, middle-aged, and younger workers–results from a systematic review. Int. J. Occup. Environ. Health 23 (2), 160–171.
Bhargava, A., Bester, M., Bolton, L., 2021. Employees' perceptions of the implementation of robotics, artificial intelligence, and automation (RAIA) on job satisfaction, job security, and employability. Journal of Technology in Behavioral Science 6 (1), 106–113.
Bisello, M., Fana, M., Fernández-Macías, E., Torrejón Pérez, S., 2021. A comprehensive European database of tasks indices for socio-economic research. In: *Labour Education and Technology JRC Series* 2021/04. European Commission, Seville.
Blinder, A.S., 2006. Offshoring: the next industrial revolution. Foreign Aff. 85, 113.
Blinder, A.S., 2009. How many US jobs might be offshorable? World Econ. 10 (2), 41.
Blinder, A.S., Krueger, A.B., 2013. Alternative measures of offshorability: a survey approach. J. Labor Econ. 31 (S1), S97–S128.
Brynjolfsson, E., Mitchell, T., 2017. What can machine learning do? Workforce implications. Science 358 (6370), 1530–1534.
Brynjolfsson, E., Mitchell, T., Rock, D., 2018. What can machines learn, and what does it mean for occupations and the economy? AEA Papers and Proceedings. 108, 43–47.
Budría, S., Milgram Baleix, J., 2020. Offshoring, job satisfaction and job insecurity. Economics: The Open-Access, Open-Assessment E-Journal 14 (2020−23), 1–32.
Calvino, F., Criscuolo, C., Marcolin, L., Squicciarini, M., 2018. A taxonomy of digital intensive sectors. In: OECD Science, Technology and Industry Working Papers 2018/14. https://doi.org/10.1787/f404736a-en.
Cardoso, M., Neves, P.C., Afonso, O., Sochirca, E., 2021. The effects of offshoring on wages: a meta-analysis. Rev. World Econ. 157 (1), 149–179.
Carlson, J.R., Carlson, D.S., Zivnuska, S., Harris, R.B., Harris, K.J., 2017. Applying the job demands resources model to understand technology as a predictor of turnover intentions. Comput. Hum. Behav. 77, 317–325.
Clark, A.E., 2015. What makes a good job? Job quality and job satisfaction. IZA World of Labor, p. 215.
Damiani, M., Pompei, F., Kleinknecht, A., 2020. When robots do (not) enhance job quality: the role of innovation regimes. SSRN Electron. J.
Delautre, G., Manrique, E.E., Fenwick, C., 2021. Decent work in a globalized economy: lessons from public and private initiatives. In: International Labour Office – Geneva: ILO.
Ebenstein, A., Harrison, A., McMillan, M., Phillips, S., 2014. Estimating the impact of trade and offshoring on American workers using the current population surveys. Rev. Econ. Stat. 96 (4), 581–595.
Egger, H., Kreickemeier, U., Wrona, J., 2015. Offshoring domestic jobs. J. Int. Econ. 97 (1), 112–125.
EWCS, 2015. Sixth European Working Conditions Survey: 2015. https://www.eurofound.europa.eu/en/surveys/european-working-conditions-surveys/sixth-european-working-conditions-survey-2015.
Eurofound, 2021. Working Conditions and Sustainable Work: An Analysis Using the Job Quality Framework, Challenges and Prospects in the EU. Publications Office of the European Union, Luxembourg.
Feenstra, R.C., Hanson, G.H., 1999. The impact of outsourcing and high-Technology capital on wages: estimates for the United States, 1979-1990. Q. J. Econ. 114 (3), 907–940.
Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The next generation of the Penn World Table. Am. Econ. Rev. 105 (10), 3150–3182 available for download at. www.ggdc.net/pwt.
Felten, E., Raj, M., Seamans, R., 2019. The occupational impact of artificial intelligence on labor: the role of complementary skills and technologies. NYU Stern School of Business. https://doi.org/10.2139/ssrn.3368605.
Fleurbaey, M., 2015. Beyond income and wealth. Rev. Income Wealth 61, 199–219.
Franssen, L., 2019. Global value chains and relative labour demand: a geometric synthesis of neoclassical trade models. J. Econ. Surv. 33 (4), 1232–1256.
Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? Technol. Forecast. Soc. Chang. 114, 254–280.
Gallie, D., Felstead, A., Green, F., 2012. Job preferences and the intrinsic quality of work: the changing attitudes of British employees 1992–2006. Work Employ. Soc. 26 (5), 806–821.
Geishecker, I., Görg, H., 2013. Services offshoring and wages: evidence from micro data. Oxf. Econ. Pap. 65 (1), 124–146.
Gimet, C., Guilhon, B., Roux, N., 2015. Social upgrading in globalized production: the case of the textile and clothing industry. Int. Labour Rev. 154 (3), 303–327.
Gisbert, J.R., Palau, C., Uriarte, M., Prieto, G., Palazón, J.A., Esteve, M., González, A., 2014. Integrated system for control and monitoring industrial wireless networks for labor risk prevention. J. Netw. Comput. Appl. 39, 233–252.
Goos, M., 2018. The impact of technological progress on labour markets: policy challenges. Oxf. Rev. Econ. Policy 34 (3), 362–375.
Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. 104 (8), 2509–2526.
Graetz, G., Michaels, G., 2018. Robots at work. Rev. Econ. Stat. 100 (5), 753–768.
Gruetzemacher, R., Dorner, F.E., Bernaola-Alvarez, N., Giattino, C., Manheim, D., 2021. Forecasting AI progress: a research agenda. Technol. Forecast. Soc. Chang. 170, 120909.
Hazlett, C., Wainstein, L., 2022. Understanding, choosing, and unifying multilevel and fixed effect approaches. Polit. Anal. 30 (1), 46–65.
Heckman, J.J., Lochner, L.J., Todd, P.E., 2006. Earnings functions, rates of return and treatment effects: the mincer equation and beyond. Handbook of the Economics of Education 1, 307–458.
Hox, J. J. 2010. Multilevel analysis. Techniques and applications. 2. Ed. New York, NY: Routledge (Quantitative Methodology Series).
Hughes, C., Robert, L., Frady, K., Arroyos, A., 2019. Artificial intelligence, employee engagement, fairness, and job outcomes. In: Managing Technology and Middle-and Low-Skilled Employees. Emerald Publishing Limited.
Hummels, D., Munch, J.R., Xiang, C., 2018. Offshoring and labor markets. J. Econ. Lit. 56 (3), 981–1028.
Kim, C.H., Sakamoto, A., 2008. The rise of intra-occupational wage inequality in the United States, 1983 to 2002. Am. Sociol. Rev. 73 (1), 129–157.
Kim, S., Christensen, A.L., 2017. The dark and bright sides of personal use of Technology at Work: a job demands – resources model. Hum. Resour. Dev. Rev. 16 (4), 425–447.
Koopman, R., Wang, Z., Wei, S.-J., 2014. Tracing value-added and double counting in gross exports. Am. Econ. Rev. 104, 459–494.
Lane, M., Saint-Martin, A., 2021. The impact of artificial intelligence on the labour market: what do we know so far? OECD Social, Employment and Migration Working Papers No. 256. https://doi.org/10.1787/7c895724-en.
Ledić, M., Rubil, I., 2021. Beyond Wage Gap, Towards Job Quality Gap: The Role of Inter-Group Differences in Wages, Non-Wage Job Dimensions, and Preferences. Social Indicators Research, pp. 1–39.
Lee, J., Gereffi, G., Lee, S.-H., 2016. Social upgrading in Mobile phone GVCs: Firm-level comparisons of working conditions and labour rights. In: Nathan, D., Tewari, M., Sarkar, S. (Eds.), Labour in Global Value Chains in. Cambridge University Press, Asia Cambridge, pp. 315–352.
Lesener, T., Gusy, B., Wolter, C., 2019. The job demands-resources model: a meta-analytic review of longitudinal studies. Work Stress 33 (1), 76–103.
Lewandowski, P., Park, A., Hardy, W., Du, Y., Wu, S., 2022. Technology, skills, and globalization: explaining international differences in routine and nonroutine work using survey data. World Bank Econ. Rev. 36 (3), 687–708.
Maas, C.J.M., Hox, J.J., 2005. Sufficient sample sizes for multilevel modeling. Methodology 1 (3), 86–92.
Mahapatra, M., Pati, S.P., 2018. Technostress creators and burnout: a job demands-resources perspective. In: Proceedings of ACM SIGMIS-CPR'18, pp. 70–77.
Marcolin, L., Miroudot, S., Squicciarini, M., 2016. The Routine Content of Occupations: New Cross-Country Measures Based on PIAAC, OECD Science, Technology and Industry Working Papers, 2016/02. OECD, Paris.
Milberg, W., Winkler, D., 2011. Economic and social upgrading in global production networks: problems of theory and measurement. Int. Labour Rev. 150 (3–4), 341–365.
Mira, M.C., 2021. New model for measuring job quality: developing an European intrinsic job quality index (EIJQI). Soc. Indic. Res. 1–21.
Nadvi, K., Thoburn, J.T., Thang, B.T., Ha, N.T.T., Hoa, N.T., Le, D.H., Armas, E.B.D., 2004. Vietnam in the global garment and textile value chain: impacts on firms and workers. J. Int. Dev. 16 (1), 111–123.
Nikulin, D., Wolszczak-Derlacz, J., 2022. GVC involvement and the gender wage gap: Micro-evidence on European countries. Struct. Chang. Econ. Dyn. 63, 268–282.
Nikulin, D., Wolszczak-Derlacz, J., Parteka, A., 2022. Working conditions in global value chains. Evidence for European employees. Work Employ. Soc. 36 (4), 701–721.
Nuutinen, S., et al., 2022. How job resources influence employee productivity and technology-enabled performance in financial services: the job demands–resources model perspective. Journal of Organizational Effectiveness 9 (2), 233–252.
OECD, 2017. OECD Guidelines on Measuring the Quality of the Working Environment. Organisation for Economic Co-operation and Development, Paris.
OECD, 2022. OECD AI Observatory. OECD, Paris. https://www.oecd.ai/.
Parteka, A., Wolszczak-Derlacz, J., 2019. Global value chains and wages: multi-country evidence from linked worker-industry data. Open Econ. Rev. 30 (3), 505–539.
Parteka, A., Wolszczak-Derlacz, J., 2020. Wage response to global production links: evidence for workers from 28 European countries (2005–2014). Rev. World Econ. 156, 769–801.
Peeters, M.C., Plomp, J., 2022. For better or for worse: The impact of workplace automation on work characteristics and employee well-being. In: Petrillo, A., De Felice, F., Achim, M.V., Mirza, N. (Eds.), Digital Transformation - Towards New Frontiers and Business Opportunities. IntechOpen. https://doi.org/10.5772/intechopen.102980.
Rossi, A., 2013. Does economic upgrading Lead to social upgrading in global production networks? Evidence from Morocco. World Dev. 46, 223–233.
Salanova, M., Llorens, S., Ventura, M., 2014. Technostress: The dark side of technologies. In: The Impact of ICT on Quality of Working Life. Springer, Dordrecht, pp. 87–103.
SES, 2014. Structure of Earnings Survey 2014. Eurostat. https://ec.europa.eu/eurostat/cache/metadata/en/earn_ses2014_esms.htm.
Shen, L., Silva, P., 2018. Value-added exports and US local labor markets: does China really matter? Eur. Econ. Rev. 101, 479–504.
Spitz-Oener, A., 2006. Technical change, job tasks, and rising educational demands: looking outside the wage structure. J. Labor Econ. 24 (2), 235–270.
Stier, H., Yaish, M., 2014. Occupational segregation and gender inequality in job quality: a multi-level approach. Work Employ. Soc. 28 (2), 225–246.
Szymczak, S., Wolszczak-Derlacz, J., 2022. Global value chains and labour markets – simultaneous analysis of wages and employment. Econ. Syst. Res. 34 (1), 69–96.
Szymczak, S., Parteka, A., Wolszczak-Derlacz, J., 2022. Position in global value chains and wages in central and eastern European countries. Eur. J. Ind. Relat. 28 (2), 211–230.
Tarafdar, M., Tu, Q., Ragu-Nathan, B.S., Ragu-Nathan, T.S., 2007. The impact of technostress on role stress and productivity. J. Manag. Inf. Syst. 24 (1), 301–328.

Timmer, M., Los, B., Stehrer, R., De Vries, G., 2016. An Anatomy of the Global Trade Slowdown Based on the WIOD 2016 Release, GD-162. Groningen Growth and Development Centre, University of Groningen.
Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J., 2015. An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. Rev. Int. Econ. 23, 575–605.
Turja, T., Särkikoski, T., Koistinen, P., Krutova, O., Melin, H., 2022. Job well robotized!–maintaining task diversity and well-being in managing technological changes. Eur. Manag. J.
UNIDO, 2020. UNIDO's Industrial Development Report 2020. Industrializing in the digital age. United Nations Industrial Development Organization. https://www.unido.org/resources-publications-flagship-publications-industrial-development-report-series/idr2020.
Van Ark, B., Erumban, A., Corrado, C., Levanon, G., 2016. Navigating the new digital economy. In: Driving Digital Growth and Productivity from Installation to Deployment. The Conference Board, New York.
Van Ark, B., de Vries, K., Erumban, A., 2019. Productivity and Innovation Competencies in the Midst of the Digital Transformation Age. A EU-US Comparison. European Economy Discussion Paper, p. 119.
Visser, J., 2019. ICTWSS Database. Version 6.0. Amsterdam Institute for Advanced Labour Studies (AIAS), University of Amsterdam, Amsterdam.
Wang, Z., Wei, S.J., Zhu, K., 2013. Quantifying international production sharing at the bilateral and sector levels. National Bureau of Economic Research No. w19677 (revised February 2018).
Webb, M., 2020. The Impact of Artificial Intelligence on the Labor Market. https://www.michaelwebb.co/webb_ai.pdf.
Williams, M., 2013. Occupations and British wage inequality, 1970s–2000s. Eur. Sociol. Rev. 29 (4), 841–857.
WIPO, 2019. WIPO Technology Trends 2019: Artificial Intelligence. World Intellectual Property Organization, Geneva. https://www.wipo.int/edocs/pubdocs/en/wipo_pub_1055.pdf.
WIOD, 2021. World Input-Output Database 2016 Release, 2000-2014. https://doi.org/10.34894/PJ2M1C. DataverseNL, V2.

Aleksandra Parteka is Associate Professor at the Faculty of Management and Economics at Gdańsk University of Technology. Her research interests include: international economics; the impact of trade, integration, and technological progress on labour markets and productivity, economic growth. She is currently involved in a Horizon-Europe project "Rethinking Global Supply Chains: measurement, impact and policy" (Rethink-GSC), and, as Principal Investigator, in a project funded by the National Science Centre on "Technological specialisation and productivity divergence in the age of digitalisation, automation and AI".

Joanna Wolszczak-Derlacz is Associate Professor at Gdańsk University of Technology, Poland. Her research interests focus on the theory and empirics of economic convergence, productivity and efficiency analysis, economics of education and labour markets. She has led research projects on GVC/GSC-labour market interactions and efficiency of higher education institutions, and is currently involved in Horizon-Europe project "Rethinking Global Supply Chains: measurement, impact and policy (Rethink-GSC)". She was a member of the Council of the Polish National Science Centre (NCN), 2018–2022.

Dagmara Nikulin is Assistant Professor at Gdańsk University of Technology, Faculty of Management and Economics. Her research interests focus on labour economics, informal employment and international economics. Recently she has been involved in projects related to the impact of GVC on the labour market as well as in research explaining the extent and determinants of different types of informal work, including false self-employed.