DELIVERABLE 5.1

ANALYSING THE SOCIO-ECONOMIC CONSEQUENCES OF THE TECHNOLOGICAL TRANSFORMATION

EU-wide empirical evidence from three combined employer-employee datasets

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 822296.

Document Summary

Document type: *Deliverable 5.1*

Title: *Analysing the socio-economic consequences of the technological transformation*

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Reviewer/s: *Sylvie Hamon-Cholet*

Date: *May 2023*

Document status: *Final*

Forword

This deliverable is a compilation of five reports dedicated respectively to the first five tasks of WP 5, namely:

- Task 5.1: Structural transformation of employment and labour markets
- Task 5.2: Structural transformation of occupations, tasks and skills
- Task 5.3: The rise of the platform economy
- Task 5.4: Structural transformation of working time and work-life balance
- Task 5.5: Structural transformation of occupational risks and quality of working life

The document is organised as follows:

The following summary synthetises all the results and findings presented in this compiled document.

Summary from the results of WP5

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1. Conceptual frame

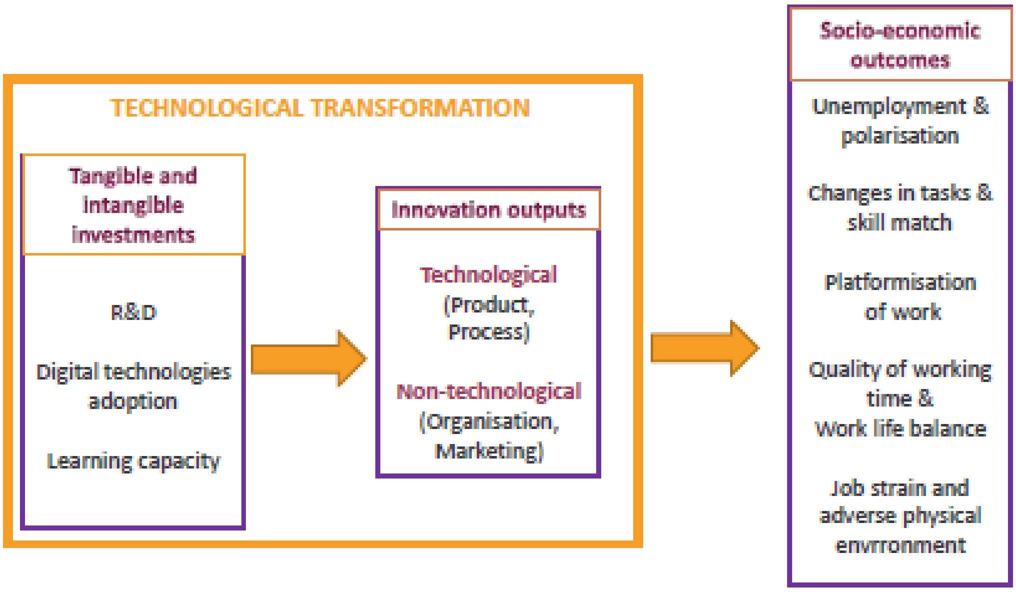
We view the technological transformation, not only as the inclusion of digital technologies into the production process but also as a relationship embedded in the production process, sometimes called the **knowledge production function** that relates inputs in which firms invest with innovation outputs. **Digital technologies** are one of these inputs, together with **R&D expenditures**.

We add a third input to this knowledge production function: the **learning capacity of the organisation**. The learning capacity of an organisation is its ability to adapt and compete at low cost through learning. It is related to the skills, management tools and organisational practices that support individual and organisational learning. An organisation that invests heavily in learning capacity is a learning organisation. It promotes **innovative work behaviour of employees** that stimulates innovation without directly consuming scarce environmental resources.

Specifically, we measure the **Learning capacity of an organisation** using a composite indicator based on **eight dimensions**: preservation of the cognitive dimension of work, training opportunities, worker autonomy in cognitive tasks, motivation backed by the organisation, autonomous teamwork practices, social support, supportive supervisory style and direct worker participation.

In terms of innovation output, we use the traditional distinction between **product** and **process** innovations, considered in Schumpeterian approaches as **technological innovations** and used to study the growth dynamics of the manufacturing sector. We also address **marketing** and **organisational** innovations, which are forms of non-technological innovation more often encountered in the service sector. We further examine different combinations of innovation with the idea that **combinations of technological and non-technological forms of innovation** reflect more advanced innovation strategies based not only on the inclusion of new technologies in the production process, but also on a revision of the organisational paradigm to better align with the set of new opportunities it opens.

We then examine the relationship between the technological transformation and a range of **socio-economic outcomes**, as shown in the graph below. We first look at labour market outcomes at the sectoral level, in particular **unemployment** and indicators of **job polarisation** that show whether the occupational structure is shifting towards better or lower paid jobs. We then turn to sectoral measures of **changes in tasks** and **skill mismatches**. After that, we examine the quality of working life by focusing first on **job strain** and **adverse physical working environments** and then on the **quality of time** and **work-life balance** issues. Finally, we address the development of **platformised forms of work** where the lack of time and procedural autonomy is reinforced by digital surveillance.



Our empirical results are based on the analysis of **three combined databases integrating EU wide employer and employee level surveys.** Data integration occurs at a meso level, using a key cell where we aggregate information, which is, in the first two databases, a one-digit sector in a country in a year and, in the third one, a size class (10-50 employees or 50 and more employees) in a one-digit sector in a country. They respectively cover 2010-2019 (CIS-CICT-EWCS-LFS), 2013-2015 (ECS-CIS-CICT-ESENER) and 2019 (ECS-LFS). We find the following main results on the consequences of investments in the **Learning capacity** and in **Digital technologies**.

2. Findings on the investment in Learning capacity

- The **investment into the Learning capacity of the organisation** is a **win-win strategy** leading to **more innovativeness** and a **high road** of **improved socio-economics outcomes**.
    - Higher Learning capacity favours **all forms of innovation.**
    - In terms of combination of innovations within firms, a higher Learning capacity favours **non-technological innovations only** and **combinations of technological and non-technological innovations**, but not technological innovations only.
    - Higher Learning capacity is also related with more **labour market resilience**, in particular less unemployment and less occupational downgrading.
    - In sectors with higher Learning capacity employees have **higher quality of working life**. They are less exposed to the platformisation of work, to low working time autonomy and to involuntary part time work.
- **Combined** with high levels of Digital technology adoption and use, a high Learning capacity of the organisation **accelerates innovation** and **tends to curb negative outcomes** of technology uses.
    - It allows for a **more parsimonious use of skills.**
    - It reduces **occupational restructuring.**

    - In terms of **job strain and adverse physical environment**, discussions on health and safety issues promote lower psychological job demands and environmental risks in highly digitalised work environments, while having self-managed teams promotes greater autonomy.
- There are **four points of attention** associated with the Learning capacity of the organisation:
    - **Firms' innovation strategies have a mediating** role on the effect of the Learning capacity on **labour market outcomes** and on the **quality of working time**. These effects are most of the time partial, they do not jeopardise and sometimes they even strengthen the overall positive effect of the Learning capacity.
        - On **labour market outcomes, product innovation fully mediates** the effect of the Learning capacity of organisations by protecting against the evolution of the occupational structure towards the bottom of the wage hierarchy. It **partially mediates** the effect of the Learning capacity on unemployment rates with a reducing impact and on job upgrading by favouring a shift of the occupational structure toward middling and high paid jobs.
        - On **the quality of working time**, product innovation and marketing innovation partially mediate the effect of the Learning capacity on low working time autonomy and involuntary part time work, the former with a reducing impact, the latter with an augmenting one. Organisational innovation has the same mediation effect as marketing innovation except for the ability of choosing the start and end time of the working day.
    - Higher Learning capacity induces **more interferences of professional life with personal life,** these negative effects being partially attenuated by process and organisational innovation.
    - Higher learning capacity is **skill demanding**: in sectors where the Learning capacity of organisations increases, more employees feel that they need further training to cope well with their duties.
    - The Learning capacity of the organisation relies on **contextual or workplace related skills** and its development is not contingent on the educational attainment of the workforce, but a matter of work organisation. High Learning capacity should not be the privilege of organisations with a highly educated workforce. Indeed, the development of **elite learning organisations** would lead to labour market segmentation and increased inequality.
- In most sectors, the level of the Learning capacity of the organisation has **been stagnating** over the last decade. **Barriers to the development of the Learning capacity of organisations** need to be addressed.
    - The **Nordic institutional model** seems more suited to the development of the Learning capacity of the organisation questioning the existence of institutional barriers.
        - **Trust** between employers and employees are an important ingredient for the sharing of knowledge, giving a strong role to **social dialogue.**

        - **Enabling forms of organisations** allowing for experimentations and failures are needed as well as long term and multi-stakeholders' perspectives.
        - Skills **acquired through professional experience** have to be valorised
    - Preserving the **capacity to generate new knowledge** could become challenging in contexts of **digital monitoring**.

3. Findings on the investment in digital technologies

- The **investment in digital technologies** has been rapidly increasing everywhere between 2010 and 2019, with southern, central and eastern European countries on a catching up path with the rest of the EU. The Covid crisis however may have adversely affected this convergence process.
- Digital technology adoption and use by sectors, as R&D and Learning capacity, favours **innovativeness.**
    - Higher digital intensity favours **all forms of innovation.**
    - In terms of combination of innovations within firms, a higher digital intensity favours **technological innovation only** and **combined technological and non-technological innovation**, but not non-technological innovation only.
    - When combined with R&D investments, Digital technology adoption and use **accelerates all types of innovation** except process innovation, and **all forms of combination between technological and non-technological innovations** except non-technological innovation only for which the impact of the interaction is negative.
- The **socio-economic outcomes** associated with digital technologies adoption and use are **more mixed** than the ones associated with the learning capacity of the organisation.
    - **On the positive side,** we find outcomes in terms of **job strain and adverse physical environment.**
        - Sectors with higher digital intensity have **less strenuous work environment**: they are associated with lower levels of emotional demand, higher levels of autonomy, less lifting and tiring positions and less environmental risks.
    - On the **negative side**, we find changes in tasks and skills, platformisation of work and more sitting at work.
        - In sectors where **digitalisation has progressed**, employees are more likely to see an **increase in their tasks and duties**, but they also more often feel that they have the necessary skills **to cope with more demanding tasks**.
        - The **development of platformised forms of work** that we observe in highly digitalised sectors could explain this paradoxical experience, in particular when the Learning capacity of organisations is low. We also find that the technologies, which are the more strongly related with platformisation, are data analytics and robots.

        - Sectors with higher Digital technology adoption and use also have a workforce that is **more sedentary**.
- The **socio-economic outcomes** associated with the adoption and use of digital technologies are relying more heavily **on the innovation strategy** adopted by firms than what we have observed in the case of the Learning capacity of the organisation. Most of the time, the innovation type **fully mediates** the relationship between Digital technologies and the considered outcome. Product innovation and marketing innovation have marked effects, albeit in opposite directions when the effects of process and organisational innovation are weaker and more nuanced.
    - **Product innovation mediates positively** the relationship between Digital technology adoption and use and socioeconomic outcomes. At the sector level, it is associated with **less unemployment, less occupational downgrading, a shift of occupational structure towards middling and best paid jobs, less low working time autonomy and less involuntary part-time work**.
    - The mediation effect of **marketing innovation** is **clearly the opposite**: it induces in digitally intensive sectors more unemployment, less occupational upgrading, more occupational downgrading, more low working time autonomy, more involuntary part-time work and more work-related contacts during leisure time.
    - **Process and organisational innovation mediates positively** the relationship between Digital technology adoption and the **interferences of professional life with personal life**.
    - **Organisational innovation mediates negatively** the relationship between Digital technology adoption and use and the **possibility to take hours off for family or personal reasons**.
- **Overall** investments in **Digital technologies** may lead to a **high** or to a **low road** depending on the **Learning capacity** of the organisation and its **innovation strategy**. A high Learning capacity associated with product innovation and, to a lesser extent process innovation favours the high road when low Learning capacity, marketing innovation and, to a lesser extent organisational innovation leads to the low road.

BEYOND 4.0

PART A - TASK 5.1
STRUCTURAL TRANSFORMATION OF EMPLOYMENT AND LABOUR MARKET

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Deliverable type version: D5.1 – May 2023
Associated Work Package: WP5
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WP leader: Nathalie Greenan

beyond4.0.eu

European Commission

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 822296.

Document Summary

Document type:	*Deliverable D5.1 – Part C*
Title:	*Structural transformation of employment and the labour market.*
Author/s:	*Ylenia Curci, Nathalie Greenan, Silvia Napolitano*
Reviewer/s:	*Steven Dhondt*
Date:	*May 17, 2023*
Document status:	*Final*

Abstract

This report presents the main findings from TASK 5.1 (structural transformation of employment and labour market), in which the links between the technological transformation and the labour market outcomes have been investigated through a unique dataset at the EU-wide level over 2010-2016. By providing improved measures to proxy the technological transformation, the report offers new evidence about the relationship between innovation inputs, innovation outputs and outcomes in the labour market. The improved measures of technological change include (1) a direct measure of investments in technology adoption and use that takes into account the evolutionary nature of ICTs and digital technologies; (2) a composite indicator measuring the learning capacity of organisations; (3) an extended measure of innovation that comprises product, process, marketing and organisational innovation as well as their combination at the firm level (Section 2). The investigated labour market outcomes are the unemployment rates (Section 3.1) and indicators of polarisation (Section 3.2).

Content

Executive Summary

This report investigates the links between the technological transformation and the labour market outcomes.

As a first step, it describes the technological transformation by mobilising the Beyond 4.0 integrated database CIS-CICT-EWCS. This dataset is a EU-wide cross-country and cross-sector dataset that combines through a “common cell”, which is an industry in a country in a given year, three main data sources: two employer-level data sources, the Community innovation survey and the Community ICT usage and e-commerce in enterprises survey (Eurostat), and an employee level one, the European Working Conditions Survey (Eurofound). As a second step and with the aim to provide new evidence about the relationship between technological transformation and labour market outcomes, we further enrich the Beyond 4.0 integrated database by adding the Labour Force Survey (Eurostat), a household-level survey.

Inspired by the knowledge production function in the CDM model (Crépon et al., 1998), we describe the technological transformation in the digital age as the relationship between different innovation inputs able to increase the stock of knowledge within companies and innovation outputs. On the input side, we consider the role of R&D and we develop a synthetic indicator of *Digital technologies adoption and use* that takes into account the heterogeneity of ICTs and digital technologies and their constant renewal. Then, we add a new argument, the *Learning capacity of the organisation*, which proves to be a distinct and impactful dimension of the knowledge production function. The learning capacity captures the adoption of management tools and organisational practices concerned with the improvement of individual and organisational learning. On the output side, we consider an extended measure of innovation that includes technological (product and process innovation) and non-technological innovations (organisational and marketing innovation) as well as their combinations to account for more complex forms of outputs from innovative activities in the digital age.

We then move towards the analysis of the nexus between the technological transformation and labour market outcomes. We step into the debate about the fear of massive skills and job destruction due to automation, robotics and Artificial Intelligence (AI) in the current digital revolution. Emerging digital technologies seem to affect workers in all industries and across different occupational ranks. Nevertheless, each technological revolution also generates new goods and services that, by raising demand, create new jobs that use new skills.

We focus on two specific outcomes. The first one is the unemployment rates at the country-sector level, which thus refer to the loss of employment of people who were employed in a specific sector, but who, despite being available for work and having taken specific steps to find a job, have not been recruited in their former sector or in another one. The second one refers to indicators of polarisation that accounts for the change in the share of employment at the sector-country level for occupations belonging to the first, second or third tercile of a wage ranking distribution with respect to a base year (2011).

Our results show that investing in the *Learning capacity of the organisation* and in *Digital technologies* stimulates innovativeness in enterprises. All types of innovation are favoured as well as all types of firm-level combinations of innovation except technological innovations only for the *Learning capacity* and non-technological innovations only for *Digital technologies adoption and use*.

However, these two types of investments influence on labour market outcomes differently. The effect of investments in *Digital technology adoption and use* are fully mediated by innovation while mediation is either partial or nil for investments in the *Learning capacity of the organisation*. In particular, this latter investment provides direct protection against unemployment and, in the longer run, against occupational downgrading.

This result aside, innovation plays an important role in determining the labour market outcomes of technological transformation. We find that, depending on its characteristics, innovation can be either beneficial or detrimental to employees.

Product innovation is for the good as it mediates positively the relationship between the *Learning capacity* and *Digital technologies* and labour market outcomes. Higher levels investments are related with less unemployment and occupational downgrading and more occupational upgrading. This result suggests the dominance of a market expansion effect in sectors where a larger share of firms introduce goods or services that are new or significantly improved with respect to their characteristics or intended uses.

Marketing innovation is for the bad as its mediation effect on labour market outcomes is opposite. However, it mainly concerns *Digital technologies adoption and use*. For the *Learning capacity of the organisation* we only find no mediation for outcomes at t+2 and a partial mediation between 28% and 40% for changes in the occupational structure at t+3. This result suggests the predominance of a business stealing effect in the sectors of companies that introduce significant changes in product design, packaging, placement, promotion or pricing to the detriment of employees in companies that do not.

Overall, we find two main results. First, investing into the learning capacity of the organisation appears as a win-win strategy leading to more innovativeness and improved labour market outcomes. Second, even though labour market outcomes depend on the relative shares of product and marketing innovations, the technological transformation over the second decade of the millennium is not associated with increased polarisation. In sectors where investments in *Digital technologies* and *Learning capacity* lead to a share of product innovative firms which is larger than that of marketing innovative firms, unemployment rates are lower and the job structure shifts upward in the wage ranking. On the contrary, when marketing innovation dominates, sector level unemployment develops and low paid jobs grow to the detriment of the best paid ones.

1 Introduction

This report investigates the links between the technological transformation and the labour market outcomes. In particular, it provides:

- A framework to better understand and describe the technological transformation, which includes: first, a direct measure of investments in technology adoption and use that takes into account the diversity of ICTs and digital technologies as well as their constant renewal; second, a measure of the learning capacity of organisations as a distinct argument of the knowledge production function of enterprises able to capture the implementation of those management tools concerned with the improvement of individual and organisational learning; third, an extended measure of innovation that includes, along with technological innovation, non-technological innovations and combinations of the two (Section2.1).
- New evidence, at the EU-wide level, about the relationship between innovativeness, technology adoption and learning capacity of the organisations (Section 2.2).
- New evidence, at the EU-wide level, about the relationship between the technological transformation and two labour market outcomes that the literature often relates to the technological transformation: unemployment rates (Section 3.1) and polarisation of the labour market (Section 3.2).

It uses the EU-wide dataset constructed in WP3, which aggregates data at the country-sector level to combine employer and employee-level sources. The dataset is used in a flexible way in order to obtain, for every objective of the task, the richest possible coverage of EU countries and sectors. The dataset to describe the technological transformation is indeed enriched with another household level source, the Labour Force Survey, which provides information on employment trajectories, unemployment, job flows and job wage rankings.

2 Describing the technological transformation with a EU-wide combined dataset[1]

The fifth technological revolution has started in the 1970s with the entry into the age of Information and Telecommunication (Perez, 2003). Since the big bang of the announcement of the Intel microprocessor in Santa Clara, the Information and Communication Technologies (ICTs) revolution has accelerated three times: with the generalisation of the personal computer, with the entry into the Internet age and today with the progress in AI. However, those economies that have invested heavily in ICTs have not yet entered a phase of accelerated and inclusive growth.

To understand this puzzle, we look for a missing element in our current understanding of the technological transformation in the digital age. The literature about productive complementarities (Milgrom and Roberts, 1990) points to the existence of synergies among

[1] This section of the report is further developed in Greenan and Napolitano (2023).

technological choices and organisational and skills-related practices. Indeed, by exploiting a unique dataset from macroeconomic sources on the US non-farm business sector between 1948 and 2007, Corrado and Hulten (2010) have demonstrated that a major shift in the composition of investments and capital formation towards intangibles had occurred. When adopting ICTs and digital technologies, organisations face a number of options on how to embed them into the organisation in order to take advantage of the opportunities they open and innovate. In particular, they need to build synergies by combining them with other tangible and non-tangible investments while directing their productive effort towards new goods and services, new organisational forms and business models. A complex process of investment in technological expertise, product design, market development and organisational learning is generating the knowledge that is the source of today’s growth. Hence, the key skill for organisations is not only technical nor purely incorporated in the individual, it is a collective skill, built in the workplace and allowing the orchestration of knowledge from various fields of expertise. However, the pioneering researches that have adopted this vision have focused on productivity while we want to address innovation issues.

We thus refer to the theoretical frame of the knowledge production function in the so-called CDM model, developed by Crépon, Duguet and Mairesse (1998). It gives a good description of how technological transformation takes place within companies. In the most advanced version of this model, firms invest in R&D and ICTs to increase the stock of productive knowledge, a latent variable that translates into innovation outputs, with product and process innovations being the two types of innovations generally considered. We explore firms’ investments and capabilities to adopt and use new technologies and their effects on innovation outputs by augmenting this knowledge production function in three main directions.

First, on the input side, along with the traditional drivers of innovation such as R&D expenditure, we enrich the direct measurement of ICT investments. We develop a synthetic indicator that takes into account the heterogeneity of ICTs and digital technologies and their constant renewal. We expect that investment in ICTs and digital technologies drives innovation, and we test whether this is especially true when technology investments are combined with R&D expenditure and other intangible investments.

Second, again on the input side, we add the learning capacity of the organisation as a new argument in the knowledge production function. The learning capacity captures the adoption of management tools and organisational practices concerned with the improvement of individual and organisational learning. In particular, we refer to the concept of “organisational learning” that is key in understanding the capability of an organisation to process new knowledge and to nimbly adapt to it: a learning organisation is able to create, acquire, transfer, integrate knowledge, to distribute it among its members as well as to encourage employees to develop innovative work behaviours (Jerez-Gomez et al., 2005; Greenan and Lorenz, 2010). The economic and management literature stresses that learning organisations are adaptive. They have the managerial capacity to design and adjust business models in rapidly changing environments, without disrupting their structure, thus preserving their inertial forces and ensuring their sustainability (Teece, 2018). In this sense, organisational learning is a dynamic process of strategy renewal, which involves a number of trade-offs between exploration, new opportunities, innovation and change on the one side and exploitation, established practice, continuity, routinisation and standardisation on the other one (Greenan and Napolitano, 2021). The relation between innovativeness, technology adoption and human and organisational capital is something still scantly explored by the empirical literature (Bresnahan, Brynjolfsson and Hitt, 2002; Greenan, 2003; Bloom et al., 2019). We aim to provide some new evidence in this respect, assuming that the learning capacity is an important driver of innovation and that its combination with ICTs and digital technologies is likely to generate synergetic effects. Indeed, improving skills endowments as well as implementing managerial practices that incentivise employees' innovative work behaviour can foster the implementation of new technologies and facilitate the absorption of externally available knowledge (Piva and Vivarelli, 2009). It is this second way of increasing the knowledge production function that makes our contribution the most original.

Third, we enlarge the definition of innovation outputs to include non-technological forms. Indeed, we consider four types of innovation outputs – product, process, organisational and marketing – as well as their combination to account for more complex forms of outputs from innovative activities in the digital age. The notions of innovation outputs and their measurement are drawn from the Oslo Manual (OECD/Eurostat, 2005), which is the reference manual to tackle the various facets of the potential change resulting from the technological transformation. The manual summarises how organisations have managed to be creative by taking advantage of the new opportunities opened up by the digital revolution.

To provide empirical evidence about this augmented knowledge production function, we built a unique dataset at EU-wide level over the years 2010-2016. The construction of the dataset required substantial effort, which is core in the value added of our contribution. It combines, through a "common cell", that is an industry in a country in a given year, three main data sources: two employer-level data sources, the Community innovation survey and the Community ICT usage and e-commerce in enterprises survey (Eurostat) and an employee level one, the European Working Conditions Survey (Eurofound). This dataset allows us to develop our enriched measurement frame of the ongoing technological transformation with the three desired novelties: a synthetic indicator of *Digital technology adoption and use* that takes into account the diversity of ICTs and digital technologies as well as their technological intensity, a composite indicator of the *Learning capacity of the organisation* based on information gathered at the employee level and combined measures of technological and non-technological innovations within industries. To our knowledge, Nicoletti et al. (2020) are the first that have made such an attempt to link employer with employee-level surveys with the aim of better understanding the diffusion of digital technologies.

2.1 Technological transformation through the lenses of the knowledge production function

Our analysis builds on the construction of a cross-country and cross-sector dataset based on the integration of employer and employee level EU-wide surveys that allow exploring the relations between company-level decisions and characteristics of the economy, at a meso level (Greenan et al., 2023). The final dataset covers enterprises with more than 10 employees and employees in the same size class of enterprises in 32 countries (the EU 27 Member States, plus North Macedonia, Norway, Serbia, Turkey and the UK); 11 sectors (the NACE Rev. 2 at 1-digit level, sections C to N, but with sections D and E aggregated), and 3 time periods (2010-2012, 2012-2014, 2014-2016). This wide country and sectoral coverage allows taking into account those differences due to the market structure, the policy drivers and the macroeconomic patterns that shape the technological transformation, which are overviewed when looking at a macro level. As well, it allows taking into account reallocation and selection effects across firms, which cannot be assessed focusing on individual-level data.

Another key characteristic of the constructed dataset is that it gathers information both at the employers' and the employees' level from three different surveys, taking advantage of the richness of having two different and complementary sources of information.

Table 1: Key measures and related sources of data

	Measures	Source of data	Available years	Level of information
INPUTS at *t-2*	R&D expenditures	Statistics on Business enterprise R&D expenditure (aggregated data, Eurostat)[2]	2010, 2012, 2014	Employers
	Digital technology adoption and use	Community survey on ICT usage and e-commerce in enterprises (aggregated data, Eurostat)[3]	2010, 2012, 2014	Employers
	Learning capacity of the organisation	European Working Condition Survey (EWCS, Eurofound)	2010, (2012 imputed), 2015	Employees
OUTPUTS at *t*	Innovation outputs	Community Innovation Survey (aggregated data, Eurostat)[4]	Δ2010-2012 Δ2012-2014 Δ2014-2016	Employers

Table 1 summarises the sources of data and the related key measures that they provide. The first enterprise-level source is the Community ICT usage and e-commerce in enterprises survey (Eurostat), which yearly provides direct measures on the use of Information and Communication Technologies and e-commerce in European enterprises. It is a central survey to measure the digital revolution. Because of confidentiality issues, Eurostat releases only the aggregated data at the country and sector levels. We gather data about the adoption rates, at the country-sector-year level as well as at the European level, of a number of specific technologies and we construct a synthetic indicator of *Digital technology adoption and use*.

The second enterprise-level source is the Community Innovation Survey (Eurostat), carried out every two years. It provides information on different types of innovation outputs, defined on the basis of the conceptualisation provided by the Oslo Manual (OECD/Eurostat, 2005), as well as on various aspects concerning the companies' innovation activity, such as the

[2] https://ec.europa.eu/eurostat/databrowser/view/rd_e_berdindr2/default/table?lang=en
[3] https://ec.europa.eu/eurostat/web/digital-economy-and-society/data/comprehensive-database
[4] https://ec.europa.eu/eurostat/web/science-technology-innovation/data/database

cooperation with other organisations or the award of public financial support. We use these data to identify the innovation outputs as well as some controls for our models. The aggregated dataset provided by Eurostat ensures EU-wide coverage and fine (at 2-digit) sectoral-level information. While the CIS also provides information about R&D expenditure, we prefer to use another specific source from Eurostat, the Statistics on Business enterprise expenditure on R&D (BERD by NACE Rev. 2 activity), because the level of information is more complete: data are collected through random samples or censuses, as well as from administrative registers or through a combination of sources and the information is provided on a yearly basis.

The third source is the European Working Conditions Survey (EWCS, Eurofound), which is targeted at employees or self-employed individuals. The EWCS is an essential survey for understanding the forms of work organisation that stimulate creativity, human development through improved skills and meaningful work, and feelings of trust and fairness. We use this source of information to construct a composite indicator of the *Learning capacity of the organisation*.

The three datasets are used in an integrated manner. We combine them through a "common cell", constructed on key variables (country, sector and year) present in all the surveys and harmonised[5].

The Digital technology adoption and use indicator

Digital technology is pervasive, and it is rapidly being adopted by organisations, even if with significant differences depending on their nature (Yoo et al., 2012). Table 2 gives the diffusion rates at the EU level and their evolution from 2010 to 2014. There are also significant differences across countries and industries (Remes et al., 2018). Figure 1 shows that even for mature technologies such as access to the internet, in some sector-country observations, the rate of diffusion remains relatively low (the minimum is 67%). For other technologies such as mobile broadband connection, technologies for online purchases, customer relationship management software or social networks, the range is close to 90%, pointing to large inequalities in diffusion across sectors and countries.

We construct a synthetic indicator of *Digital technology adoption and use* through the available direct measures of digital technology use from the Community ICT usage and e-commerce by enterprises. As we are interested in the years 2010, 2012 and 2014, the selection of variables is driven by the data availability for these three years.

We calculate indicators of digital intensity, taking into account both the use and the novelty of the technology: the percentage of enterprises that adopted the technology in a given industry within a country is weighted using the inverse of the European diffusion rate for each technology, which proxies its technological intensity. In so doing, those technologies that are reaching their exhaustion point have lower weights, while emerging technologies have higher ones. As shown in Table 2, the diffusion rate for cloud computing and social networks in 2010

[5] See Table A1 in appendix for information on the coverage of each surveys.

and 2012 are in italic. This is because these technologies were not yet included in the questionnaire. Questions about them appear for the first time in 2014. We imputed the maximum weight for these emerging technologies in 2010, as they had a null diffusion rate, and the inverse of the mid-value between 0 and the diffusion rate of 2014 for 2012.

The overall *Digital technology adoption and use* index is the sum of the indicators built for each of the five sub-dimensions of digital technologies identified in Table 2. It equals the normalised sum of the weighted rates of technology diffusion at the country-sector level. It varies from 0.41 to 95.22 according to the within sector rate of diffusion of the set of ICTs and digital technologies and to its degree of novelty[6]. If this indicator makes the best use of existing direct measures of new technologies, the technological transformation approach adds further information with the measurement of product and process innovation. For instance, in the period under study, AI or robots were not yet measured in the survey on ICT usage and e-commerce as they were emerging technologies. However, they are likely to have been quoted as product innovation by the firms that were developing them or process innovation by the frontier firms that were experimenting their inclusion into the production process.

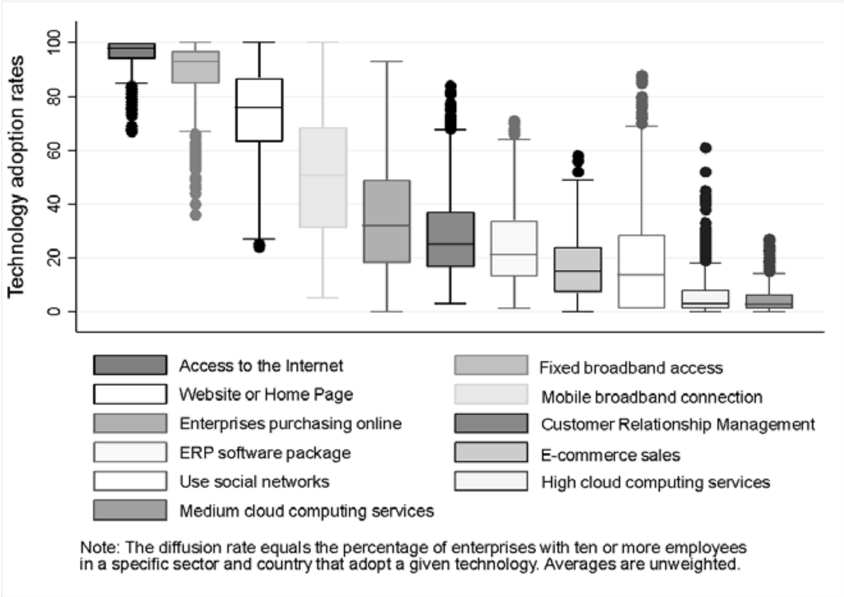
Table 2: The Digital technology adoption and use dimensions and diffusion rates at the EU level in 2010, 2012 and 2014

			EU diffusion rates *(imputations in italic)* 2010	2012	2014
Basic technologies	E-commerce	Enterprises purchasing online	37%	34%	38%
		E-commerce sale (web sales)	15%	16%	18%
	Connection technologies	Access to the Internet	94%	95%	97%
		Fixed broadband access	84%	90%	92%
		Mobile broadband connection (3G modem or 3G handset)	27%	49%	64%
	Web and Social media technologies	Website or Home Page	67%	71%	74%
		Use social networks (e.g. Facebook, LinkedIn, Xing, Viadeo, Yammer, etc.)	*0%*	*16,5%*	33%
	E-business technologies	ERP (Enterprise Resource planning) software package to share information between different functional areas	21%	22%	31%
		Customer Relationship Management (CRM)	25%	*27,5%*	30%
Emerging technologies	Cloud computing	High CC services (accounting software applications, CRM software, computing power)	*0%*	*4,5%*	9%
		Medium CC services (e-mail, office software, storage of files, hosting of the enterprise's database)	*0%*	*4,5%*	9%

Source: Beyond 4.0 integrated database CIS-CICT-EWCS (2010, 2012 and 2014)
Coverage: EU27 plus North Macedonia, Norway, Serbia, Turkey and the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

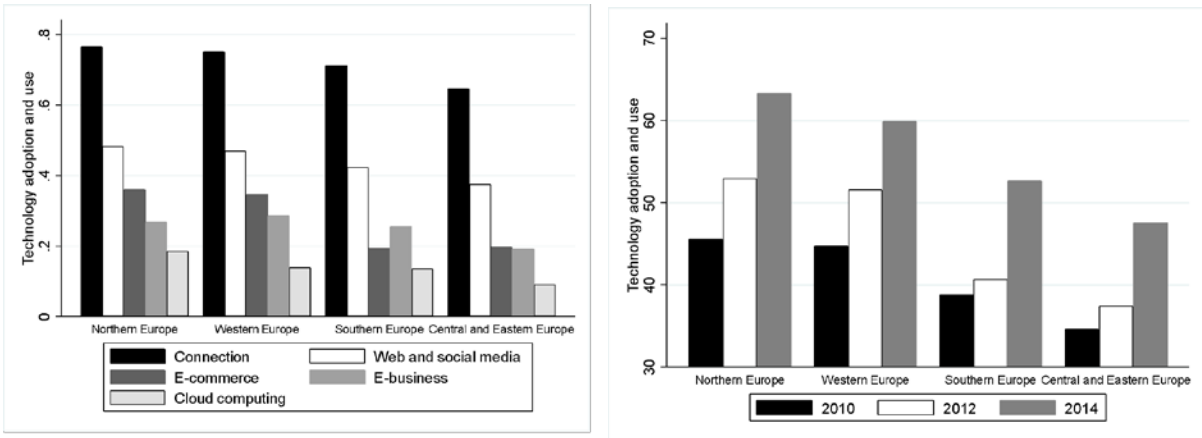
[6] See summary statistics in Table A2 and A3 in the appendix.

Figure 1: Diffusion rate of different digital technologies at the country-sector level



Source: Beyond 4.0 integrated database CIS-CICT-EWCS (2010, 2012 and 2014)
Coverage: EU27 plus North Macedonia, Norway, Serbia, Turkey and the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Figure 2: Average Digital technology adoption and use indicator by geographical groups and in time



Source: Beyond 4.0 integrated database CIS-CICT-EWCS (2010, 2012 and 2014)
Coverage: EU27 plus North Macedonia, Norway, Serbia, Turkey and the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

In Figure 2, we observe the distribution of the *Digital technology adoption and use* indicator between different geographical groups[7]. The ranking of the sub-dimensions does not change considerably between these groups: connecting technologies are the most widely spread, followed by web and social media, e-commerce, e-business and cloud computing. One

[7] The composition of geographical groups is given in Table A2 in appendix.

exception is, however, noticeable: e-business technologies (ERP and CRM) are relatively more diffused in Southern and Central-Eastern Europe as they rank third in the first geographical group and are as spread as e-commerce in the second. When we consider the overall indicator, Northern and Western countries show higher average levels than Southern and Central-Eastern countries. As well, when looking at the evolution of the indicator between 2010 and 2014, we see that Digital technology adoption and use is rapidly increasing in all groups of countries with one difference. In Northern and Western Europe this rise was quite steady when sectors in Southern and Central-Eastern Europe seem to catch up in 2014 after a sluggish growth between 2010 and 2012.

The indicator of Learning capacity of the organisation

We develop the *Learning capacity* indicator to measure the ability of an organisation to develop management tools and organisational practices aimed at improving individual and organisational learning. We refer to the notion of "learning organisation", defined as an entity capable of adapting and competing at low cost through learning. A learning organisation promotes the individual learning of workers by encouraging them to develop innovative work behaviours, fostering their autonomy and initiative, and providing training opportunities. Furthermore, through its organised framework, knowledge is also shared and distributed among members, a culture of innovation is supported, and trade-offs between the competing goals of exploration and exploitation are resolved through a dynamic process of strategy renewal (Greenan and Lorenz, 2010; Greenan and Napolitano, 2021).

The indicator is constructed with data from the EWCS 2010 and 2015. We identify eight sub-dimensions of the learning capacity of an organisation in line with the organisational psychology approach to innovative work behaviour and workplace innovation (Janssen et al., 2004; Jerez-Gómez et al., 2005; Costantini et al., 2017).

1. **Preservation of the cognitive dimension of work**, which measures whether worker’s job involves solving unforeseen problems, performing complex tasks and learning new things;
2. **Training opportunities**, which measures whether the worker undergone on-the-job training or training paid for or provided by the employer to improve their skills;
3. **Autonomy of worker in cognitive tasks**, which measures whether worker’s job involves assessing the quality of own work and applying own ideas in work;
4. **Motivation backed by the organisation**, which measures whether the employee agrees that the organisation motivates workers;
5. **Autonomous teamwork**, which measures whether, when teamwork is implemented, the team members decide by themselves for the task division, for the head of the team and for the timetable;
6. **Social support**, which measures whether colleagues and management provide help and support;

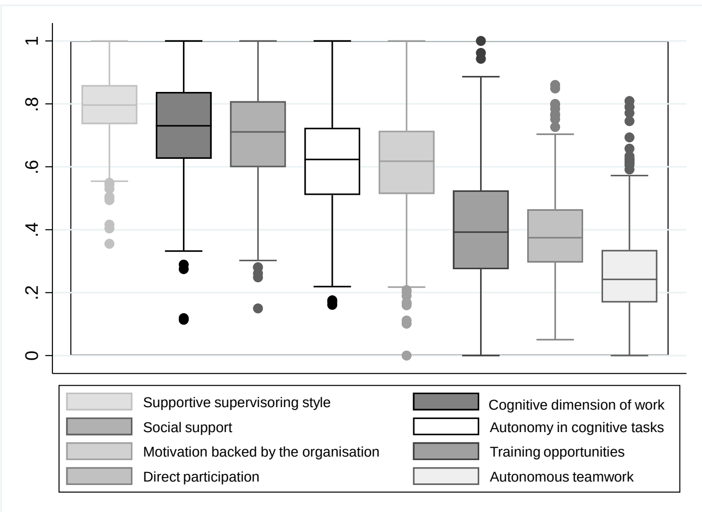
7. **Supportive supervisory style**, which measures whether the manager/supervisor provides feedback on work, respects the worker as a person and is good at resolving conflicts;
8. **Direct participation**, which measures whether the worker has a say in the choice of working partners, is consulted to set targets, is involved in improving work processes and can influence decisions.

The **Learning capacity of the organisation indicator** is constructed at the individual level, on the population of workers employed in organisations with more than 10 employees. The composite indicator equals the normalised sum of the 8 sub-dimensions, where each dimension has the same weight. The Cronbach's alpha coefficient among the sub-dimensions equals 0.80, suggesting that the items have relatively high internal consistency[8].

We then proceed with the aggregation of data at the “common cell” level. As the EWCS provides two points in time, the 2010 and the 2015, we imputed the value of the *Learning capacity* indicator for the 2012-2014 period as the midpoint between the two years. The final *Learning capacity* indicator equals the average *Learning capacity* in a specific country-sector-year level. Values vary from 29.62 to 88.89 (Table A3 in the appendix), and Figure 3 shows that there is great variation between different sector-country observations.

Figure 4 gives the distribution of the *Learning capacity* indicator between geographical groups. First, the ranking of the sub-dimensions is similar within the different groups; second, Northern and Western countries have higher average levels of *Learning capacity* than Central-Eastern and Southern countries. When looking at the evolution of the indicator between 2010 and 2015, we further note the stagnation of the average level of *Learning capacity* in the four geographical groups.

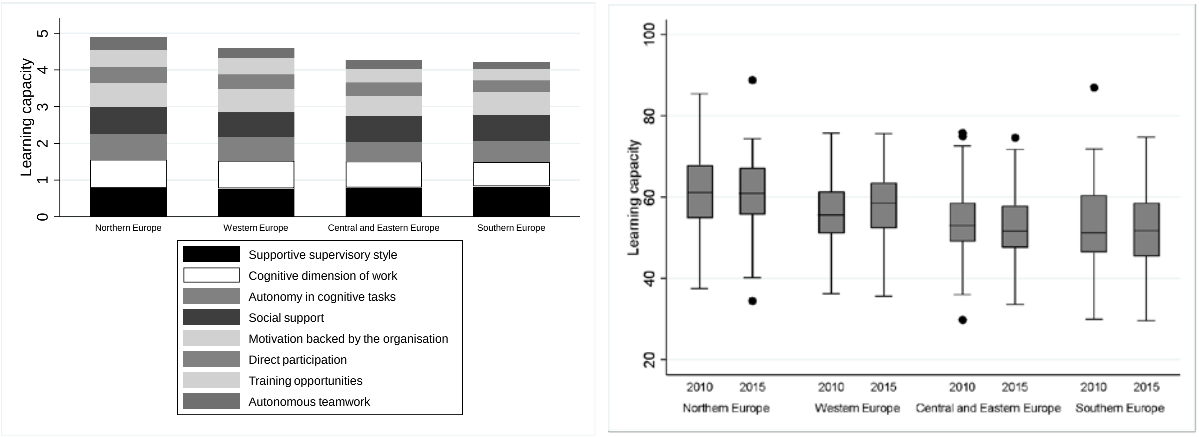
Figure 3: Distribution of the learning capacity sub-dimensions at the country-sector level



Source: Beyond 4.0 integrated database CIS-CICT-EWCS (2010, 2015)
Coverage: EU27 plus North Macedonia, Norway, Serbia, Turkey and the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

[8] See summary statistics and correlation matrix in Table A5 in the appendix.

Figure 4: Average Learning capacity indicator by geographical groups and in time



Source: Beyond 4.0 integrated database CIS-CICT-EWCS (2010, 2015)
Coverage: EU27 plus North Macedonia, Norway, Serbia, Turkey and the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

2.2 Econometric analysis of the technological transformation

We measure the determinants of innovation outputs econometrically, describing a knowledge production function where inputs determine innovation outputs. The adopted specifications of the model are the following:

I. $Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \varepsilon_{ijt}$
II. $Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{ijt}$
III. $Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \beta_6 X_{ijt} + \varepsilon_{ijt}$
IV. $Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \beta_4 Learn_{ijt-2} * Tech_{ijt-2} + \beta_5 R\&D_{ijt-2} * Tech_{ijt-2} + \beta_6 X_{ijt} + \varepsilon_{ijt}$

Where i are sectors according to the NACE Rev. 2 classification at 1-digit level, j are countries and t is time. In the first specification, we only include R&D and the *Digital technology adoption and use* indicator, while we augment the second one with the *Learning capacity indicator* which is original with respect to the literature about the determinants of innovation. In a third specification, we included some controls. In a fourth specification, we add the interaction terms between the *Learning capacity* and the *Digital technology adoption and use* indicators and between R&D and the Digital technology adoption and use indicator. All specifications include as controls country and time dummies as well as a dummy differentiating between the secondary (C to F, D-E aggregated) and tertiary (G to N) sectors.

The variable $Inno_{ijt}$ represents the sector level share of enterprises in a given country that introduced a new or significantly improved product, production process, organisational method, marketing concept or strategy[9] between three different periods: 2010-2012, 2012-

[9] The Oslo Manual (OCDE/Eurostat, 2005) defines: “A product innovation is the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics.” (p. 48); “A process innovation is the implementation of a new or significantly

2014 and 2014-2016. It may stand as well for the share of enterprises which introduced a combination of different types of innovation outputs: product and/or process innovative enterprises regardless of organisational and marketing innovations; product and/or process innovative enterprises only; organisation and/or marketing innovative enterprises regardless of product and process innovations; organisation and/or marketing innovative enterprises only; product and/or process innovative enterprises AND organisation and/or marketing innovative enterprises only. Basically, these different aggregates allow distinguishing between enterprises introducing technological (product and/or process) and non-technological innovation (organisational and/or marketing innovations), as well as to identify enterprises implementing a combination of technological and non-technological innovations (OECD/Eurostat, 2005).

The explanatory variables are lagged two years with respect to innovation outputs in order to characterise the date just before the start of the two years innovation period. The $R\&D_{ijt}$ variable is the logarithm of the expenditure for research and development per employee, in thousands of euros, in the calendar year. The $Tech_{ijt}$ variable is the *Digital technology adoption and use* indicator. The $Learn_{ijt}$ variable stands for the Learning capacity indicator. X_{ijt} is a matrix of controls drawn from the CIS. The average size of enterprises takes into account the fact that larger enterprises may be able to invest more. The share of enterprises that receive public financial support and the share of enterprises that cooperate on (product and/or process) innovation activities with other enterprises or organisations reflect the opportunities to share knowledge, to lower risks and costs and to benefit from knowledge spillovers (Mairesse and Mohnen, 2010).

We implement a Weighted Least Squares (WLS) estimator, where weights are the number of employees in the cell, in order to account for the differing sizes of industries within countries (Wooldridge, 2010).

Table 3 shows the results of the specified models for what concerns the share of product, process, organisation and marketing innovative enterprises and Table 4 for what concerns the share of enterprises that introduced combinations of technological and non-technological innovation outputs.

First, results show that R&D expenditures have a significant effect on all types of innovation outputs. This is in line with the previous literature that suggests that R&D efforts lead to successful innovation by generating new knowledge (Hall et al., 2010). In terms of magnitude, a 1 point rise in the R&D expenditure per employee increases by between 0.01 and 0.02 percentage points (pp) the share of innovative enterprises when only one type of innovation is considered (model III). Looking at the possible combinations of innovation outputs, the increase in R&D effort has a positive impact on the share of product and/or process innovative firms and on the share of organisation and/or marketing innovative firms by about

improved production or delivery method. This includes significant changes in techniques, equipment and/or software." (p. 49); "A marketing innovation is the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing." (p. 49); "An organisational innovation is the implementation of a new organisational method in the firm's business practices, workplace organisation or external relations." (p. 51).

0.02 pp, independent of the introduction of other types of innovations. By contrast, it is less relevant, but still significant, for product and/or process innovative enterprises only, while it is not significant for organisation and/or marketing innovative enterprises only. Overall, a 1 point rise in R&D expenditure has a positive impact of 0.015 pp on the share of innovative enterprises introducing a combination of product and/or process innovations and organisational and/or marketing innovations (model III).

A rise of 1 point in the *Digital technologies adoption and use* index is particularly relevant for the share of product innovative enterprises, with an impact in the model III of 0.22 pp, while it is lower for the share of organisation (0.12 pp) and marketing (0.17 pp) innovative enterprises. Results are not stable across the different specified models for process innovative enterprises. Nonetheless, looking at combinations of innovations allows shedding more light on this regard: increased *Digital technology adoption and use* have a positive and significant impact on the share of product and/or process innovative enterprises of 0.26 pp and on the share of organisation and/or marketing innovative enterprises of 0.19 pp, regardless any other types of innovations (model III). By contrast, for the share of product and/or process innovative enterprises only and for the share of organisation and/or marketing innovative enterprises only, the effect is respectively small and non-significant. When technological and non-technological innovations are combined (as shown by the share of product and/or process innovative enterprises AND organisation and/or marketing innovative enterprises) a 1 point increase in *Digital technology adoption and use* has a positive impact of around 0.17 pp (model III). These results confirm that ICTs and digital technologies are important drivers of innovation as they enable and facilitate knowledge production.

What does the *Learning capacity of the organisation* index bring to this picture of the innovative activities of European enterprises? First, as one can see by comparing the results of models I and II, the *Learning capacity* index adds information to the analysis, without substantially altering R&D and *Digital technology adoption and use coefficients*. The significant and positive effect of the *Learning capacity* index shows that innovation is not only a matter of having more highly qualified people dedicated to R&D. It also depends on having forms of work organisation favouring innovative work behaviour and creativity throughout the whole workforce.

The *Learning capacity of the organisation* is significant for all types of innovative enterprises, but it is especially relevant for the share of organisation innovative enterprises, with an impact of around 0.26 pp for a 1 point increase (model III). It also favours combinations of innovations: a 1 point increase in *Learning capacity* has a significant and positive impact of around 0.15 pp on product and/or process innovative enterprises and of 0.26 pp on organisation and/or marketing innovative enterprises (regardless of any other form of innovation). It also shows a significant effect of 0.17 pp when technological and non-technological innovations are combined. By contrast, it has a minor effect on the share of non-technological innovative enterprises only (0.07 pp), while it is not significant for the share of technological innovative enterprises only (model III).

Table 3. WLS with robust standard errors and number of employees as weights

	Share of Product innovative enterprises				Share of Process innovative enterprises				Share of Organisation innovative enterprises				Share of Marketing innovative enterprises			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
R&D exp. per employee (ln, th. euro)	2.705*** (13.01)	2.398*** (11.04)	2.203*** (7.82)	2.118*** (7.73)	1.655*** (11.03)	1.470*** (9.07)	1.259*** (5.66)	1.278*** (5.64)	1.463*** (8.55)	0.886*** (5.58)	1.184*** (5.49)	1.060*** (5.08)	1.507*** (7.59)	1.240*** (6.11)	1.300*** (4.96)	1.250*** (4.71)
Digital technology adoption and use	0.265*** (5.24)	0.246*** (4.96)	0.224*** (3.79)	0.229*** (4.10)	0.079** (2.10)	0.063* (1.67)	0.054 (1.13)	0.048 (1.07)	0.083** (2.03)	0.048 (1.29)	0.118*** (3.12)	0.122*** (3.35)	0.148*** (3.25)	0.129*** (2.87)	0.169*** (3.13)	0.170*** (3.19)
Learning capacity of the organisation		0.203*** (3.73)	0.148** (2.44)	0.145** (2.41)		0.164*** (3.83)	0.120** (2.41)	0.109** (2.20)		0.414*** (9.54)	0.262*** (5.77)	0.276*** (6.21)		0.187*** (3.84)	0.150*** (2.65)	0.147** (2.56)
Learning capacity:Technology				0.009** (2.57)				0.008*** (2.91)				0.006** (2.53)				0.006* (1.84)
R&D:Technology				0.041*** (3.52)				0.009 (1.14)				0.018** (2.38)				0.022** (2.17)
Average size of enterprises			0.011 (1.50)	0.011 (1.46)			0.022*** (3.21)	0.023*** (3.23)			0.028*** (3.72)	0.027*** (3.69)			0.011* (1.66)	0.011 (1.62)
Share of enterprises receiving public financial support			0.159*** (3.41)	0.104** (2.35)			0.103*** (2.80)	0.081** (2.25)			-0.001 (-0.03)	-0.019 (-0.56)			0.014 (0.32)	-0.017 (-0.41)
Share of enterprises engaged in cooperation for innovation activities			-0.006 (-0.11)	0.013 (0.27)			0.049 (1.13)	0.057 (1.33)			0.098** (2.40)	0.120*** (3.10)			-0.014 (-0.30)	-0.002 (-0.05)
Tertiary sectors (ref: secondary sectors)	2.851*** (3.38)	2.354*** (2.72)	4.169*** (4.10)	3.309*** (3.41)	-1.846*** (-2.62)	-2.433*** (-3.48)	-0.744 (-0.90)	-1.054 (-1.30)	3.233*** (4.42)	1.813*** (2.65)	2.487*** (3.52)	1.990*** (2.94)	5.026*** (6.52)	4.449*** (5.80)	4.458*** (4.77)	4.025*** (4.43)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant																
Observations	578	578	486	486	581	581	486	486	581	581	486	486	581	581	486	486
Adjusted R^2	0.600	0.600	0.623	0.651	0.731	0.757	0.742	0.736	0.665	0.696	0.770	0.760	0.592	0.598	0.551	0.560

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. WLS with robust standard errors and number of employees as weights

	Share of Product and/or process innovative enterprises				Share of Product and/or process innovative enterprises only				Share of Organisation and/or marketing innovative enterprises				Share of Organisation and/or marketing innovative enterprises only				Share of Product and/or process AND organisation and/or marketing innovative enterprises			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
R&D exp per employee (ln, th. euro)	3.072***	2.749***	2.462***	2.428***	0.856***	0.893***	0.715***	0.713***	1.874***	1.407***	1.677***	1.644***	-0.160	-0.309***	-0.133	-0.113	2.132***	1.776***	1.575***	1.523***
	(14.59)	(12.44)	(9.84)	(9.76)	(10.29)	(10.00)	(6.57)	(6.54)	(8.16)	(6.44)	(6.32)	(6.03)	(-1.58)	(-2.89)	(-1.13)	(-0.97)	(11.42)	(9.79)	(7.11)	(6.98)
Digital technology adoption & use	0.269***	0.248***	0.264***	0.260***	0.061***	0.064***	0.036*	0.036*	0.146***	0.087*	0.192***	0.191***	-0.033	-0.044**	0.017	0.015	0.166***	0.152***	0.170***	0.175***
	(5.49)	(5.23)	(5.04)	(5.05)	(3.62)	(3.72)	(1.78)	(1.74)	(3.01)	(1.90)	(3.83)	(3.84)	(-1.50)	(-2.01)	(0.93)	(0.87)	(3.91)	(3.67)	(3.48)	(3.72)
Learning capacity of org.		0.209***	0.151***	0.147***		-0.025	-0.021	-0.020		0.369***	0.260***	0.256***		0.100***	0.066**	0.067**		0.247***	0.172***	0.168***
		(3.94)	(2.82)	(2.72)		(-1.04)	(-0.78)	(-0.75)		(6.99)	(4.52)	(4.40)		(3.68)	(2.15)	(2.19)		(5.38)	(3.43)	(3.35)
Learning capacity:Tech.				0.007**				0.000				0.008***				-0.002				0.005*
				(2.41)				(0.27)				(2.74)				(-1.20)				(1.76)
R&D:Tech.				0.025***				0.002				0.016*				-0.009***				0.026***
				(2.87)				(0.57)				(1.67)				(-2.73)				(2.85)
Average size of enterprises			0.030***	0.030***			0.002	0.002			0.025***	0.025***			0.004	0.004			0.017**	0.017**
			(5.11)	(5.07)			(0.55)	(0.55)			(3.33)	(3.30)			(1.56)	(1.57)			(2.26)	(2.22)
Share of ent. receiving public financial support			0.189***	0.153***			0.117***	0.114***			-0.021	-0.048			-0.075***	-0.063***			0.077*	0.041
			(5.43)	(4.39)			(6.00)	(5.57)			(-0.47)	(-1.14)			(-4.15)	(-3.38)			(1.95)	(1.06)
Share of ent. engaged in cooperation for innovation activities			-0.085**	-0.072**			-0.033	-0.033			0.033	0.046			0.036	0.032			0.052	0.064
			(-2.27)	(-1.97)			(-1.61)	(-1.59)			(0.70)	(0.98)			(1.57)	(1.40)			(1.26)	(1.59)
Tertiary sectors (ref: secondary sectors)	-0.886	-1.456*	1.157	0.560	-2.608***	-2.536**	-1.607**	-1.650***	3.795***	2.700***	2.625***	2.182**	1.655***	1.372***	0.557	0.746*	1.756**	1.055	2.080**	1.504*
	(-1.10)	(-1.78)	(1.20)	(0.60)	(-7.04)	(-6.76)	(-3.75)	(-3.87)	(4.41)	(3.30)	(2.78)	(2.32)	(4.25)	(3.45)	(1.38)	(1.83)	(2.57)	(1.56)	(2.52)	(1.88)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country dummie	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	558	558	478	478	575	575	483	483	584	584	486	486	578	578	486	486	574	574	479	479
Adjusted R^2	0.802	0.805	0.836	0.844	0.610	0.610	0.692	0.692	0.821	0.830	0.852	0.856	0.435	0.450	0.441	0.449	0.798	0.714	0.699	0.716

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When we introduce the interaction term between *Digital technologies* and *Learning capacity* investments (Model IV), results in Table 3 show that, for all types of innovative enterprises, the coefficient of the interaction term is significant. Thus, scaling up the *Learning capacity of organisations* while investing in ICTs and digital technology is highly relevant for developing the innovativeness of industries. The results on the interaction terms in Table 4 further confirm that a mix of technological and non-technological innovations rests on joint investments in *Digital technology adoption and use* and *Learning capacity*.

The interaction term between R&D and Digital technology adoption and use is also highly significant for all types of innovative enterprises, except for process innovative enterprises. It is significant and positive for technological and non-technological innovative enterprises (regardless of any other type of innovation) or for a mix of them. By contrast, the coefficient is negative for non-technological enterprises only.

With respect to the controls introduced in the models, the size of enterprises has a significant and positive effect on the share of process and organisation innovative enterprises as well as on the share of enterprises introducing a mix of technological and non-technological innovations. The estimates for the share of enterprises receiving public financial support for their innovation activities is significant and positive only for the share of technological innovative enterprises and for the share of product and/or process innovative enterprises. It is instead significant but negative for the share of organisation and/or marketing innovative enterprises only. The share of enterprises engaged in cooperation for innovation activities has a positive influence on the shares of organisation innovative enterprises in Table 3, while it has a negative effect on the share of product and/or process innovative enterprises in Table 4. Finally, tertiary industries are characterised by higher shares of product, organisation and marketing innovative enterprises (Table 3) and of non-technological innovative enterprises, but by a lower share of technological innovative enterprises only (Table 4).

2.3 Conclusions

In this section, we have investigated the determinants of the innovativeness of industries across countries in the context of technological revolution based on ICTs and digital technologies. We focus on a knowledge production function - inspired by the first equation in the CDM model (Crépon et al., 1998) - to measure the effects on innovation outputs of different innovation inputs able to increase the stock of knowledge within companies. Apart from R&D and *Digital technologies adoption and use*, we introduce a new argument, the *Learning capacity of the organisation*, which proves to be a distinct and impactful dimension of the knowledge production function. We consider that this augmented knowledge production function gives a comprehensive description of the technological transformation in the digital age.

We built a unique dataset at the EU-wide level to provide some first empirical evidence about the main components of this technological transformation over 2010-2016. It combines through a "common cell", which is an industry in a country in a given year, three main data sources: two employer-level data sources, the Community innovation survey and the Community ICT usage and e-commerce in enterprises survey (Eurostat), and an employee level one, the European Working Conditions Survey (Eurofound). This dataset allows us to develop an enriched measurement frame of the ongoing technological transformation with three novelties: first, a synthetic indicator of *Digital technology adoption and use* that takes into account the diversity of ICTs and digital technologies as well as their innovativeness; second, a composite indicator of the *Learning capacity of the organisation* based on information gathered at the employee level; third, combined measures of technological and non-technological innovations within industries.

Data access and harmonisation issues have raised a number of problems. Nevertheless, using different sources in an integrated way represents a huge opportunity to examine simultaneously the behaviour of firms in terms of tangible and intangible investments, work and organisational practices, and their impacts on innovation.

In line with the CDM research tradition, we find that across European industries, investments in R&D are powerful drivers of all forms of innovation but are especially impactful for the share of product innovative enterprises and for the share of product and/or process innovative enterprises regardless of the introduction of other types of innovations. Industries that invest in ICTs and digital technologies also show more innovativeness with one exception: the share of process innovative enterprises. Looking at combinations of innovations, ICTs and digital technologies seem impactful except for the share of product and process innovative enterprises only and for the share of organisation and/or marketing innovative enterprises only.

The *Learning capacity of the organisation*, built on the creative capabilities of the whole workforce, appears as a third vital force of the innovativeness of industries, with a stronger direct influence on organisational innovation and non-technological forms of innovation (regardless of any other type of innovation).

Our results also provide evidence of synergetic effects between investments in *Digital technologies* and in the *Learning capacity of organisations*. Indeed, interaction effects between these two domains of investment are significant across all forms of innovation. It is also particularly impactful for the non-restricted combined forms of technological, non-technological and both technological and non-technological innovations, which are likely to be the most innovative ones in the digital age.

Complementarities are also found between R&D and *Digital technologies adoption and use*, for all types of innovative enterprises, with the exception of process innovations. Also, in this case, results points to the fact that a mix of technological and non-technological innovations rests on joint investments for R&D and digital technologies.

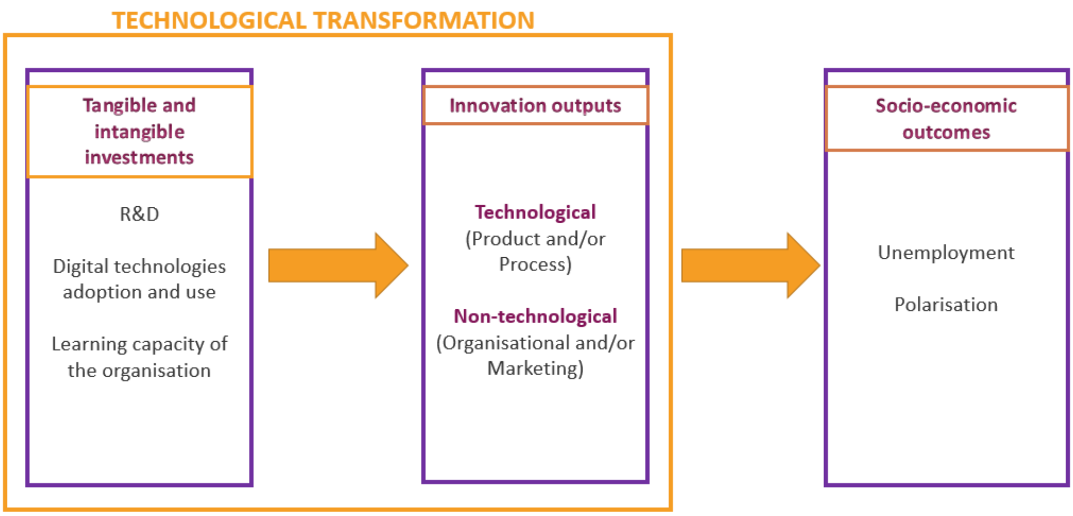
However, the descriptive evidence provides a cautionary tale with policy implications. While the adoption of ICTs and digital technologies has steadily increased in European industries between 2010 and 2016, the average *Learning capacity* of European organisations has remained stagnant. To meet the upcoming challenges of enhancing the social foundations of nations in the boundaries of the ecological ceiling (Raworth, 2017), public authorities should be concerned with the means to give a new impetus to the *Learning capacity of organisations*.

3 The labour market outcomes of the technological transformation

The nexus between technological transformation and labour market outcomes has been widely investigated, both theoretically and empirically (see Calvino and Virgillito, 2018 for a review). Periods of radical changes, such as those happening during technological revolutions, usually raise concerns about the widespread substitution of machines for labour and the rise of inequalities. The current digital revolution has spread once again the fear of massive skills and job destruction due to automation, robotics and AI (Frey and Osborne, 2017; Brynjolfsson & MacAfee, 2014). Moreover, emerging digital technologies seem to affect workers in all industries and across different occupational ranks (Bailey, 2022). Nonetheless, each technological revolution also generates new goods and services, which by raising demand, create new jobs that use new skills.

We provide evidence about the relationship between technological transformation and labour market outcomes using the Beyond 4.0 combined EU-wide dataset. In particular, we further enrich the Beyond 4.0 integrated database CIS-CICT-EWCS developed to describe the technological transformation by including the Labour Force Survey (LFS, Eurostat). This data source, which is at the household level, provides information about employment trajectories and unemployment, as well as about occupations and income levels of employed individuals. We thus use this source to measure two different socio-economic outcomes of the technological transformation: the unemployment rates and the polarisation of the labour market.

Figure 5: The theoretical framework



3.1 Technological transformation and unemployment

The economic analysis, both theoretical and empirical, has shown that the effect of innovation on employment is difficult to discern. On the one hand, technological unemployment may be caused by labour-saving process innovation, on the other hand, product innovation may foster the creation of new markets, firms or sectors and, as a consequence, new jobs. By contrast, the effects of non-technological innovation are more rarely analysed. While technological unemployment is an issue that has been present since the classical economic literature, research on non-technological forms of innovation is much more recent as it accompanies the tertiarisation of the economy. In fact, questions on non-technological innovation have only been included in the Community Innovation Survey since the 2005 edition.

As summarised by Calvino and Virgillito (2018) in their literature review, the overall effect of innovation on employment depends on the existence and type of compensating mechanisms, which are also related to the level of analysis taken into consideration.

The empirical literature shows an overall positive effect of innovation on employment level at the firm level (Pohlmeier and Entorf, 1990; Brouwer et al., 1993; Smolny, 1998; Greenan and Guellec, 2000; Harrison et al., 2014). This is usually confirmed when aggregating at the sectoral level, but with important differences depending on the level of innovativeness, the technological characteristics (Vivarelli, 2014) and the learning processes within the sectors (Pianta et al., 2022). Indeed, the sectoral level analysis allows taking into consideration that the aggregate effect of innovation on employment does not equal the average firm-level effect, as competition between firms within the same sector plays a role (Harrison et al., 2014).

In particular, the labour displacement effect deriving from process innovation becomes more apparent at the sectoral level than at the firm level. Further, the labour substitution induced by gains in productivity at the firm level (Van Reenen, 1997; Pianta, 2004; Vivarelli, 2014) may be compensated by a market expansion enabled by a price reduction, which may stimulate the demand for old products. However, at the sectoral level, it may be easier to discern whether the firm-level compensation mechanisms consist of a pure market expansion or rather in a market erosion from non-innovative firms, the so-called “business stealing”, or in firms' entry and exit flows (Harrison et al., 2014).

The effect of product innovation on employment is less ambiguous at both the firm and sectoral level. At the firm level, new products tend to create employment via a demand increase allowed by an expanding market (Van Reenen, 1997; Bogliacino and Vivarelli, 2012; Vivarelli, 2014; Marcolin et al., 2016), despite a possible counterbalancing effect of the “cannibalisation” and replacement of old products (Pianta, 2005). At the sectoral level, product innovation has a prevailing market expansion effect, thanks to job reallocation patterns within the sector (Greenan and Guellec, 2000) and especially in highly innovative industries (Mastrostefano and Pianta, 2009; Bogliacino and Pianta, 2010).

Empirical analyses that directly focus on the effects of innovation on unemployment rather than on employment creation or destruction are scanter and usually macroeconomic. Among the analysis focused on European countries, Feldmann (2013) finds a negative but temporary effect of technological change on unemployment between 1985 and 2009. Matuzeviciute et al. (2017) examine a panel of 25 EU countries between 2000 and 2012 and find no significant relationship between technological innovation and unemployment. Yildirim et al. (2022) analyse a panel dataset of 12 European countries from 1998 to 2015 and find that technological developments increase unemployment rates, both in high and relative low-innovative countries, but with higher rates in less innovative regimes.

In this study, we look at the relationship between technological transformation and unemployment, using sectoral-level data that allows capturing the compensation mechanisms described in the literature review. The measures of technological transformation and unemployment that we use allow considering that strategic choices made by organisations in terms of technological and organisational changes are among the determinants of vulnerability to non-employment of individuals (Greenan et al., 2017). Hence, we add to the literature about the innovation and employment nexus, something that is to date barely covered.

Measuring unemployment rates with a EU-wide combined dataset

With the aim to provide new evidence about the relationship between technological transformation and unemployment, we enrich the Beyond 4.0 integrated database CIS-CICT-EWCS developed to describe the technological transformation by including the Labour Force Survey (LFS, Eurostat). Table 5 summarises the sources of data and the related key measures that they provide. The LFS is a household-level survey, which provides information on the labour status of the interviewed individuals according to the ILO criteria. We are thus able to select the population of active persons.

Our measure of the share of unemployed individuals at the country-sector level is grounded on individual-level information about employment status and about transitions out of employment. Indeed, while we select the sector of activity for the employed individuals, we consider the sector of activity of the previous job for those that are currently unemployed. In doing so, we focus on a particular measure of unemployment, which refers to the loss of employment of people who were employed in a specific sector but who, despite being available for work and having taken specific steps to find a job, have not been recruited in their former sector or in another one.

Table 5: Key measures and related sources of data

	Measures	Source of data	Available years	Level of information
INPUTS at t-2	R&D exp.	Aggregated data, Eurostat	2010, 2012, 2014	Employers
	Digital technology adoption and use	Community survey on ICT usage and e-commerce in enterprises (aggregated data, Eurostat)	2010, 2012, 2014	Employers
	Learning capacity of the organisation	European Working Condition Survey (EWCS, Eurofound)	2010, (2012 imputed), 2015	Employees
OUTPUTS at t	Innovation outputs	Community Innovation Survey (CIS aggregated data, Eurostat)	2012, 2014, 2016	Employers
OUTCOMES at t+2 (& t+3)	Unemployment rates	Labour Force Survey (LFS, Eurostat)	2014, 2016, 2018 (2015, 2017, 2019)	Employees

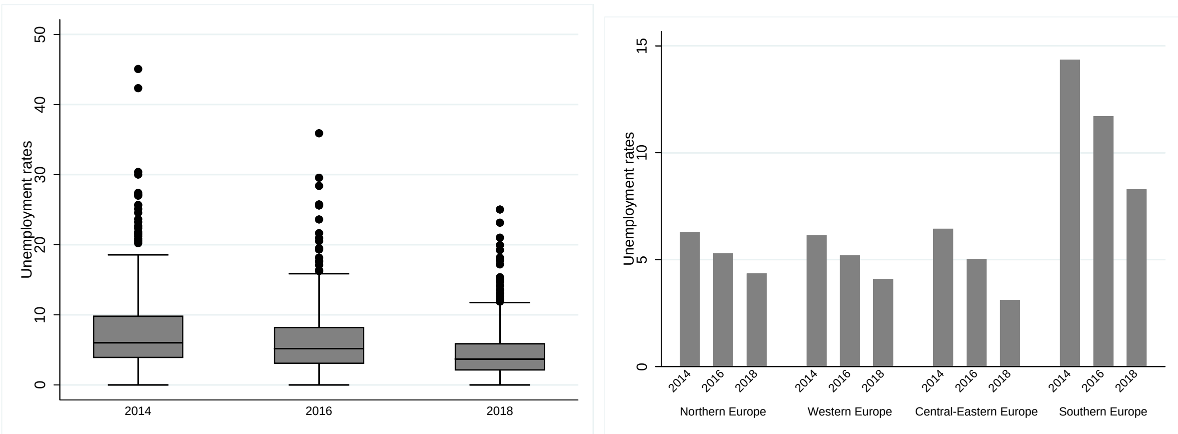
In order to maintain the time path of the Beyond 4.0 integrated database CIS-CICT-EWCS, we computed unemployment rates in 2014, 2016 and 2018 years, which is at t+2 with respect to the assessment of the innovation outputs.

Our final dataset, the Beyond 4.0 integrated database CIS-CICT-EWCS-LFS, has 908 country-sector-time period cells. It covers enterprises with more than 10 employees and their employees in 29 countries (the EU Member States, plus the UK and Norway)[10], 11 sectors (Nace Rev. 2 at 1-digit level, sectors C to N, D-E aggregated) and during 3 time periods (2010-14, 2012-16, 2014-18). Some missing cells are because the real estate sector is not covered in all countries, and that the ICT sector is not covered in Slovakia.

Unemployment rates in the selected countries and sectors in the period from 2014 to 2018 were at an average of 6,4%, with a declining trend of 3 percentage points from 2014 to 2018, as shown in Figure 6. Indeed, 2013 was the year when the unemployment rate in Europe peaked at 11% and then fell steadily in many EU countries (Eurostat).

Important variations emerge between different sectors within countries, as shown in the following graphs. Southern Europe registers the highest rates of unemployment during the entire considered period. Northern and Western Europe show similar figures.

Figure 6: Unemployment rates at the country-sector level across time



Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-2014, 2012-2016, 2014-2018)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Econometric model

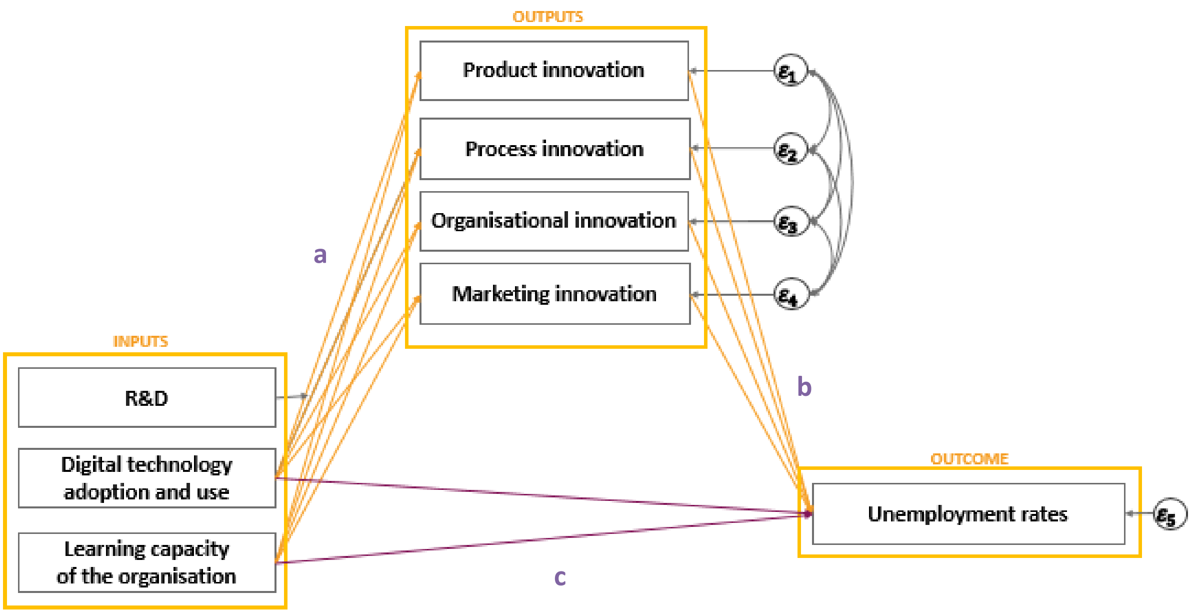
We analyse econometrically the relationship between technological transformation and unemployment rates at the country-sector level by implementing a structural equation model (SEM). It allows for simultaneously estimating multiple casual relations between the inputs of

[10] We lose 3 countries with respect to the Beyond 4.0 integrated database CIS-CICT-EWCS, not covered by LFS : Serbia, North Macedonia and Turkey.

the knowledge production function and the innovation outputs and between the inputs, the outputs and the unemployment outcome. More precisely, we implement a path analysis, which is a subset of structural equation modelling, building on the clear time ordering of the data that we use, for which we can assume that the causal relationship between variables goes in one direction only, without feedback loops. The interest in implementing a path analysis is that it allows conducting a mediation analysis, which assumes that the relationship between inputs and outcomes is mediated by a third variable, the innovation outputs of our model. Then, the influence of inputs on outcomes equals the sum of indirect (through innovation outputs) and direct effects.

The mediation analysis we implement is based on the Baron and Kenny approach adjusted by Iacobucci et al. (2007). Considering the path shown in Figure 7, when both the inputs → output path (a) and outputs →outcome path (b) coefficients are significant, there is some mediation, which can be partial or complete depending on whether the inputs → outcome path (c) is significant or not. In other words, complete mediation occurs when the size of the effect that the independent variable has on the dependent variable is no longer significant after the mediator has been introduced. Partial mediation occurs when the size of the effect that the independent variable has on the dependent variable is reduced after the mediator has been introduced.

Figure 7: The Structural Equation Model scheme



The RIT test provides the effect size on an indirect effect as the ratio of the indirect effect to the total effect, as in the following formula:

$$RIT = \frac{indirect\ effect}{total\ effect} = \frac{a * b}{(a * \ b\ ) + c}$$

The RIT value can then be interpreted as the percentage of the effect of the independent variable (e.g., *Learning capacity*) on the dependent variable (unemployment rates) mediated by the mediator variable (e.g., product innovation) (MacKinnon et al., 2007).

Our system includes the following equations:

$$\begin{cases} Product\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{1\_ijt} \\ Process\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{2_{ijt}} \\ Organisation\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{3_{ijt}} \\ Marketing\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{4\_ijt} \\ \\ Unemployment_{ijt+2} = \beta_0 + \beta_1 Tech_{ijt-2} + \beta_2 Learn_{ijt-2} + X(Inno)_{ijt} + \varepsilon_{5\_ijt+2} \end{cases}$$

Where i are sectors according to the NACE Rev. 2 classification at 1-digit level, j are countries and t is time.

The first set of regressions describes the technological transformation. We specify the most parsimonious model among the different specifications that we tested in Section 2.2 of this report. We include the *Digital technology adoption and use indicator*, the *Learning capacity* indicator and the R&D expenditures as inputs of the knowledge production function. As R&D is tested as not significantly related to unemployment rates, we do not introduce it in the last regression of the system.

The variables $Inno_{ijt}$ represent the sector-level share of enterprises in a given country that introduced new or significantly improved goods or services, production processes, organisational methods, marketing concepts or strategies.

All specifications include as controls time dummies, geographical groups dummies (see Appendix A2), and a dummy distinguishing between tertiary and secondary sectors.

In a further specification, as a robustness test, we include as control also the share of employees by educational level, considering that it can be correlated with the outcome of interest, the unemployment rates at the sector level. We distinguish between lower education (early childhood and primary education), secondary education (lower secondary, upper secondary, post-secondary non-tertiary education); higher education (short-cycle tertiary education, bachelor or equivalent, master or equivalent, doctorate or equivalent). We measure these variables using data from the LFS at time t-2, in order to reduce endogeneity issues due to the correlation between the education level and the outcome of interest, the unemployment rates.

As a supplementary robustness check, we extend the analysis by examining the persistence of the effects of technological transformations on the employment structure. We then compute the unemployment rates at t+3: 2015, 2017 and 2019.

Results

The results from the first set of equations, which specifies the relationship between inputs and innovation outputs, are similar to those presented in Section 2. Slight changes come from the reduced coverage of the combined dataset enriched with the LFS (29 countries instead of

32) and a different specification model, where we include geographical group dummies instead of country dummies. Nonetheless, the overall interpretation of results remains unchanged. We report regressions tables in Appendix A6.

The last equation of the model describes the direct effects of inputs (only *Digital technology adoption and use* and *Learning capacity*, as R&D proves to have no effect on unemployment rates) as well as the indirect effects through different types of innovation outputs on unemployment rates.

Our results in Table 6 show that *Learning capacity* reduces unemployment rates at the sectoral level. Investing in learning capacity is thus a win-win strategy: as we see in the first set of regressions (reported in Appendix A6), learning capacity stimulates innovativeness in enterprises, of all types. As shown in the SEM results, it is able as well to ensure a protective role for employees making them less vulnerable to unemployment. Consistently with previous findings at the individual level base on PIAAC (Greenan et al., 2017), we find that learning organisations decrease the probability of employees to make a transition out of employment.

Table 6. Structural Equation Model about technological transformation and unemployment rates at the country-sector level

	Unemployment rates	
	Basic model	Model for robustness
Share of product innovative enterprises	-0.062***	-0.094***
	(-2.61)	(-4.49)
Share of process innovative enterprises	-0.010	-0.009
	(-0.39)	(-0.35)
Share of organisation innovative enterprises	-0.020	-0.024
	(-0.90)	(-1.15)
Share of marketing innovative enterprises	0.066**	0.104***
	(2.28)	(3.97)
Digital technology adoption and use	-0.022*	-0.028**
	(-1.66)	(-2.18)
Learning capacity of the organisation	-0.098***	-0.157***
	(-4.98)	(-7.48)
Education (Ref: secondary education)		
Lower education		0.027
		(1.31)
Higher education		0.060***
		(4.73)
Tertiary sector (ref: secondary sectors)	-1.162***	-1.948***
	(-2.78)	(-4.26)
Geographical groups of countries	Yes	Yes
Time dummies	Yes	Yes
Constant	17.95***	18.82***
	(12.83)	(14.31)
Observations	*548*	*548*
R-sq.	*.85*	*.87*

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$
Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-2014, 2012-2016, 2014-2018)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table 7. RIT test from basic model

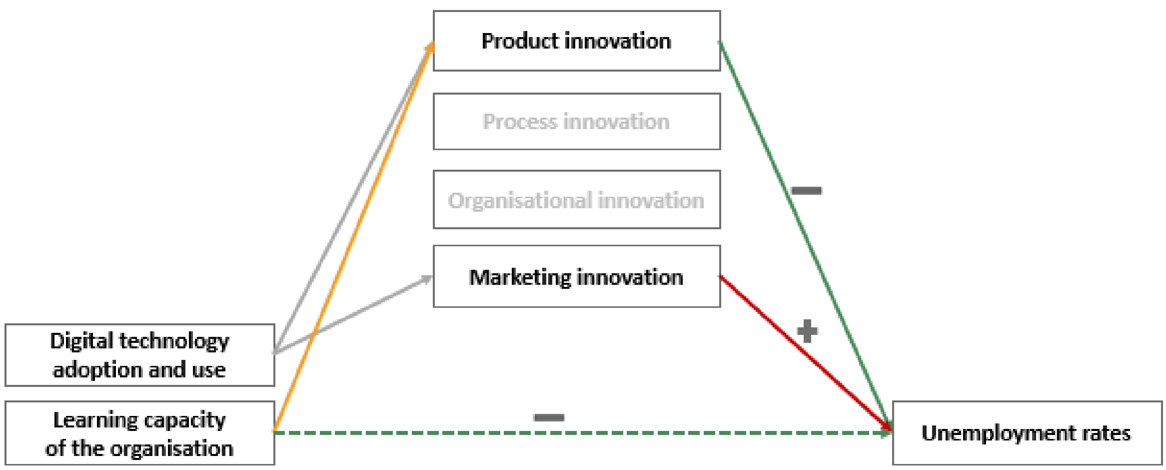
	Share of product innovative enterprises	Share of marketing innovative enterprises
UNEMPLOYMENT		
Digital technology adoption and use	Full mediation	Full mediation
Learning capacity of the organisation	7%	-

Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-2014, 2012-2016, 2014-2018)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

The influence of organisations' *Learning capacity* on unemployment rates is both direct and indirect (Figure 8). Indeed, part of its effect is mediated by product innovation (7% according to the RIT value reported in Table 7), which reinforces the protective role of the learning capacity for employees.

Digital technology adoption and use has as well a reducing effect on unemployment rates and the RIT test on the SEM shows that innovation fully mediates it. In particular, the share of product innovative enterprises completely mediates investments in digital technologies, with a total reducing effect on unemployment rates. By contrast, the share of marketing innovative enterprises attenuates the protective role of digital technologies by fully mediating it and with a total structural effect of increased unemployment rates. The overall effect of digital technologies on unemployment is thus conditional on the innovation strategy and in particular, on whether firms use digital technologies for creating new goods and services or if their use is targeted to marketing innovation without any creation of new value in goods and services.

Figure 8: Direct and indirect effects from the SEM



Note: The figure reports only relationships relevant for the analysis of the outcome. A dotted line indicates a direct relationship between inputs and outcomes ("c" type effect), solid lines indicate indirect effects ("a" and "b" type effects). A light grey innovation type box in the middle of the figure indicates no mediation effect. "a" types effects correspond to full mediation when the line is grey, partial when it is orange. "b" type effect leads to a favourable outcome when the line is green, to an unfavourable one when it is red.

We tested whether these effects persist when looking at the wider lag of time, computing the unemployment outcome at t+3 (2015, 2017 and 2019). Results, reported in Annex A7 and A8, show that the longer term effect lasts.

3.2 Technological transformation and polarisation

Beyond the historical fears of machines stealing human jobs, technology has been indicated as the cause of increasing wage inequality. One of the hypotheses fostering this allegation has been developed by Freeman and Katz (1994), who suggested that technology is a complicated matter that only skilled workers can handle. In their view, technical change is intrinsically skill-biased, favouring the creation of jobs requiring higher intellectual abilities. The implication of that is quite straightforward: technology pushes up the demand for skilled workers, hence increasing the share if high paid jobs, a phenomenon known as job upgrading.

However, skill-biased technical change is one of many hypotheses developed around the effect that technology might have on the labour market. Autor et al. (2003) proposed a bi-dimensional categorisation of the employment structure, splitting the classical skilled vs unskilled categories into routine and non-routine-based jobs. Routine manual tasks are those for which workers have been constantly replaced by machines since the first industrial revolution, while routine cognitive tasks are increasingly entrusted to computers. At the same time, non-routine tasks are mainly performed by the highly skilled workers mentioned in the Freeman and Katz hypothesis (non-routine cognitive tasks). Still, they are also a part of jobs consisting of flexible manual activities (non-routine manual tasks).

Goos and Manning (2007) take the view of the structure of employment embedded in Autor et al.'s (2003) theory and endeavour to show that technology mainly affects jobs consisting of routine tasks - which are not the least paid - while the impact on jobs involving non-routine tasks remains marginal. The authors suggest that labour market polarisation is the result of the impact of technology on a shrinking middle class (workers earning average wages), and they show this empirically using the UK data for the years 1975-1999.

Similar conclusions have been reached by Autor et al. (2006) and Acemoglu and Autor (2010) for the US labour market. Goos et al. (2009) expanded the analysis to Europe using data from the European Labour Force Survey for 1993-2006. In their paper, the authors stress the importance of investigating the phenomenon of labour market polarisation in different countries because the impact of technology on wage inequality is strongly influenced by the structure of employment itself, which in turn greatly varies in other contexts. They subsequently enriched their analysis by considering offshoring (Goos et al., 2014). Despite significant differences in the general context of the analysed countries, non-uniform impacts of routine-biased technical change and offshorability of routine tasks, they observe a quite consistent pattern of labour market polarisation across Europe.

In 2012, Fernández-Macías strongly criticised the European findings and proposed a more nuanced analysis of what happened in 15 European countries from 1995 to 2007[11]. According

[11] See also Fernández-Macías and Hurley (2017) in which the authors present findings more in line with an upgrading effect due to cognitively intense jobs.

to this author, the previous analyses have neglected the fundamental role played by the institutional framework (and its change over time) in the process of structural change in employment. Mishel and Bivens (2021) have stressed the same central institutional role for the US job market.

A more marginal stream of the literature suggests that polarisation occurs first in the direction of upgrading employment, a source of inequality that is naturally followed by higher demand for unskilled workers providing services to the rich (Mazzolari and Ragusa, 2013), hence generating a sort of polarisation cycle.

It should be noted that many of the previous studies have looked at the evolution of the structure of jobs according to their position in the wage hierarchy and have inferred a link between this evolution and technological change, identifying it with the observed time trend rather than measuring it directly. More recently, the literature has started to disentangle the factors driving labour market polarisation. Using OECD, WIOD and EU Klems data, Breemersch et al. (2019) focused on R&D intensity, ICT capital use, offshorability and China net import penetration and analysed their impact on job polarisation at the sector level. The authors show that polarisation is a phenomenon mostly happening within industries, as only one-third of it is explained by the reallocation of employment from unpolarised industries toward industries with relatively more low- and high-skill jobs. Moving away from the classical approach based on jobs (see, for instance, Frey and Osborne, 2017), this sectoral analysis allows estimating that ICT use explains about one-third of the polarisation happening within manufacturing industries, while Chinese net import competition plays a marginal role.

As one can guess by reading the literature presented above, the debate on the impact of technological change on labour market polarisation is far from being settled. While many disagree on the foundation of the issue itself (skill-biased technical change vs routine replacement positions), others stress the importance of identifying further drivers (offshoring, trade with China, institutions, firms' strategy of outsourcing). Moreover, the methodologies adopted to analyse the phenomenon range from taking technical change from granted to proxy it as a black box. The vast majority of studies consider wages as the core dimension of the quality of jobs, while some authors make use of multidimensional indicators of "good jobs'' (Oesch & Piccitto,2019).

In this study, we analyse the impact of the technological transformation on the structure of jobs by using a unique combination of data that allows us to look inside the innovation black box while considering the evolutionary nature of technological change (see Section 2 for the input-output part of the analysis). In particular, in line with Bailey (2022), we believe that the digital transformation occurring nowadays in firms is not all equal. A firm equipped with new laptops is not the same as firm using 3D printing or cloud computing, which again is not comparable to a firm buying a quantum computer. Emerging technologies continuously create opportunities for a large range of new uses and, for this reason, their adoption has no deterministic nor stable consequences. The innovation strategies and choices made by companies in how digital technologies are embedded in the production process are key in determining the impact on society. This is why we approach digital technologies using a proxy that allows taking into account their evolutionary features and the technological transformation as a relationship between inputs, including the *Learning capacity of the organisation,* and innovation outputs.

The enriched EU-wide combined dataset

To analyse labour market polarisation, we choose to focus on what happens within sectors, as the decomposition conducted by Breemersch et al. (2019) concluded that this is where most of the phenomenon occurs. To build our within-sector indicators of polarisation, we take inspiration from the methodology applied to develop the European Jobs Monitor[12] and used in Fernández-Macías (2012) and Fernández-Macías and Hurley (2017)[13]. We use data from the 2011 Labour Force Survey, which provides information about the monthly take-home pay from the main job in deciles. In our combined dataset, 2011 represents the first year of analysis[14].

To harmonise the LFS sample with the one of the Beyond 4.0 CIS-CICT-EWCS integrated database, we select the population of workers in enterprises with 10 employees and more, limited to full-timers (those working at least 30 hours per week and who self-describe as full-timers). In this population, we construct in each country a matrix of jobs, where a job is defined as an occupation (ISCO-08 at the 2-digit level) in a sector (NACE Rev 2.0, at 1-digit level).

We select our base year (2011) and our target years 2014, 2016 and 2018, which are the years that allow a 2-year lag with the output variables of the model (*product, process, organisational and marketing innovation*). We make sure that all jobs in our target years appear in the base year, and vice versa, by dropping unmatched cases.

For each interviewed individual, the LFS gives the country-based decile of the monthly take-home pay from the main job. For each job, we calculate the weighted average of the deciles by using sampling weights. Then, we rank each job from the highest to the lowest score of the deciles' average, and we compute the weighted cumulated population of this distribution. By using the midpoint of the weighted cumulated population, we create terciles (where the lowest-paid occupations are assigned to tercile 1 and the best-paid occupations to tercile 3), so that each tercile represents around 33% of the population. Table 8 shows the most represented occupations in each tercile (representing up to ~50% of the total occupations). The same occupation can appear in more than one tercile as the same occupation can be paid differently in different sectors and countries. Hence, occupations like "cleaners and helpers" appears only in the lower tercile, while customer service clerks can belong to the first and the second one.

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[12] https://www.eurofound.europa.eu/observatories/emcc/european-jobs-monitor/methodology , consulted the 25/10/2022.

[13] We are grateful to John Hurley and Enrique Fernández-Macías for their help in making their programs available to us.

[14] Unfortunately, we were not able to use 2010, which correspond to the very first year of our combined dataset, as information on occupation according to the ISCO-08 is available from 2011 on. For 2010, the occupation are classified according to the ISCO-88 classification.

Table 8. Samples of occupations in terciles 1, 2 and 3

	Freq.	Percent	Cum.
Occupations tercile 1			
91. Cleaners and helpers	220	8.56	8.56
93. Labourers in mining, construction,	194	7.55	16.12
96. Refuse workers and other elementary	175	6.81	22.93
52. Sales workers	167	6.50	29.43
42. Customer services clerks	133	5.18	34.60
41. General and keyboard clerks	116	4.52	39.12
54. Protective services workers	103	4.01	43.13
51. Personal service workers	100	3.89	47.02
Occupations tercile 2			
43. Numerical and material recording cl	165	6.64	6.64
33. Business and administration associates	157	6.32	12.96
74. Electrical and electronic trades wo	147	5.92	18.87
72. Metal, machinery and related trades	135	5.43	24.31
83. Drivers and mobile plant operators	135	5.43	29.74
41. General and keyboard clerks	126	5.07	34.81
31. Science and engineering associate p	114	4.59	39.40
42. Customer services clerks	102	4.10	43.50
71. Building and related trades workers	99	3.98	47.48
Occupations tercile 3			
12. Administrative and commercial managers	229	9.53	9.53
13. Production and specialised services	210	8.74	18.28
21. Science and engineering professionals	195	8.12	26.39
24. Business and administration profess	185	7.70	34.10
25. ICT professionals	174	7.24	41.34
11. Chief executives, senior officials	167	6.95	48.29

Source: Labour Force Survey 2011, aggregates at the job level
Coverage: Full-time employees in enterprises with 10 employees and more

On data from t+2 years (2014, 2016 and 2018), we assign each occupation in a sector-country cell to the same job-wage tercile as the one determined with the LFS 2011. Hence, the occupation-to-tercile assignment of 2011 applies for each sector-country cell across time. We then compute, by sector-country level, the employment shares in occupations belonging to each tercile of the wage ranking distribution. We are subsequently able to assess changes in the employment structure by computing the differences between the share of employment in occupations in a given tercile at time t and the shares of employment in these occupations in 2011.

Our final dataset, the Beyond 4.0 CIS-CICT-EWCS-LFS integrated database, covers twenty-seven countries (the 27 EU Member States excluding Sweden, plus the UK)[15], 11 sectors (Nace Rev. 2 at 1-digit level, sectors C to N, with D-E aggregated) and three time periods (2010-14, 2012-16, 2014-18). Table 9 summarises the sources of data and the related key measures that they provide.

[15] We lose 3 countries with respect to the Beyond 4.0 integrated database CIS-CICT-EWCS, not covered by LFS: Norway, North Macedonia and Turkey.

Table 9: Key measures and related sources of data

	Measures	Source of data	Available years	Level of information
INPUTS at t-2	R&D exp.	Aggregated data, Eurostat	2010, 2012, 2014	Employers
	Digital technology adoption and use	Community survey on ICT usage and e-commerce in enterprises (aggregated data, Eurostat)	2010, 2012, 2014	Employers
	Learning capacity of the organisation	European Working Condition Survey (EWCS, Eurofound)	2010, (2012 imputed), 2015	Employees
OUTPUTS at t	Innovation outputs	Community Innovation Survey (CIS aggregated data, Eurostat)	2012, 2014, 2016	Employers
OUTCOMES at t+2 (& t+3)	Polarisation indicators	Labour Force Survey (LFS, Eurostat)	(2011), 2014, 2016, 2018 (2015, 2017, 2019)	Employees

Econometric model

We implement a structural equation model (SEM). We use the RIT test to assess the effect size of the independent variable (e.g. *Learning capacity*) on the dependent variable (e.g. upgrading) mediated by the mediator variable (e.g. product innovation) (MacKinnon et al., 2007) (see section 3.1 for further details about this methodology).

Our system includes the following equations:

$$\begin{cases} Product\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{1\_ijt} \\ Process\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{2_{ijt}} \\ Organisation\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{3_{ijt}} \\ Marketing\_Inno_{ijt} = \beta_0 + \beta_1 R\&D_{ijt-2} + \beta_2 Tech_{ijt-2} + \beta_3 Learn_{ijt-2} + \varepsilon_{4\_ijt} \\ \\ Polarisation_{ijt+2} = \beta_0 + \beta_1 Tech_{ijt-2} + \beta_2 Learn_{ijt-2} + X(Inno)_{ijt} + \varepsilon_{5\_ijt+2} \end{cases}$$

Where i are sectors according to the NACE Rev. 2 classification at 1-digit level, j are countries and t is time.

The first set of regressions describes the technological transformation. We specify the most parsimonious model among the different specifications that we tested in Section 2.2 of this report. We include the *Digital technology adoption and use* indicator, the indicator of *Learning capacity of the organisation* and the R&D expenditures as inputs of the knowledge production function. The variables $Inno_{ijt}$ represent the sector-level share of enterprises in a given country that introduced new or significantly improved goods or services, production processes, organisational methods, marketing concepts or strategies. Results are reported in Appendix A6.

We consider three *Polarisation* indicators for a t+2 lag. The dependent variable *upgrading* accounts for the change in the share of employment at the sector-country level for occupations belonging to the third tercile of the wage ranking with respect to the base year, 2011. For instance, if in 2011 the third tercile accounted for 50% of the employment in the sector-country and in 2014 it accounts for the 60%, upgrading amounts 10 percentage points (pp), while if in 2014 it accounts for 40%, the variable upgrading amounts -10 pp. The same reasoning applies to the variable *middle-class* and *downgrading* for the second and first tercile, respectively.

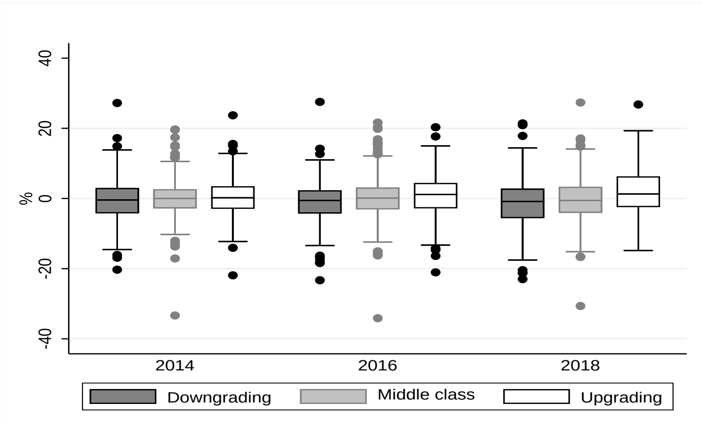
All specifications include as controls time dummies, geographical groups dummies (see Table A4 in appendix), and a dummy distinguishing between tertiary and secondary sectors.

In a further specification, we includes as control also the share of employees by educational level, considering that it can be correlated with the outcome of interest, the polarisation of the labour market. We distinguish between lower education (early childhood and primary education), secondary education (lower secondary, upper secondary, post-secondary non-tertiary education) and higher education (short-cycle tertiary education, bachelor or equivalent, master or equivalent, doctorate or equivalent). We measure these variables using data from the Labour Force Survey at date t-2, in order to reduce endogeneity issues due to the correlation between the education level and the outcome of interest.

Figure 9 shows how these dependent variables distribute across country-sector cells and time. We observe that the t+2 differences in shares span between 20 pp and -20 pp, with an average close to zero. Table 10 reports the results of the econometric analysis for the years 2014-2018. We briefly discuss the results in the following paragraph.

As a robustness check, we extend the analysis by examining the persistence of the effects of technological transformations on the employment structure. We then compute the outcomes at t+3: 2015, 2017 and 2019.

Figure 9: Differences in the share of employment in occupations in the lowest, middle and highest tercile of the wage ranking



Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-2014, 2012-2016, 2014-2018)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table 10. Technological transformation and polarisation at t+2, SEM results

	Downgrading		**Middle class**		**Upgrading**	
	Basic model	Model for robustness	Basic model	Model for robustness	Basic model	Model for robustness
Share of product innovative enterprises	-0.188***	-0.179***	0.098**	0.064	0.089**	0.113***
	(-4.38)	(-4.03)	(2.27)	(1.40)	(2.01)	(2.58)
Share of process innovative enterprises	0.030	0.032	-0.007	-0.006	-0.021	-0.023
	(0.81)	(0.91)	(-0.21)	(-0.20)	(-0.54)	(-0.66)
Share of organisation innovative enterprises	-0.056	-0.053	-0.018	-0.030	0.069*	0.075**
	(-1.42)	(-1.39)	(-0.48)	(-0.81)	(1.82)	(2.09)
Share of marketing innovative enterprises	0.127***	0.121***	-0.014	-0.006	-0.113***	-0.118***
	(3.37)	(3.10)	(-0.38)	(-0.15)	(-3.19)	(-3.45)
Digital technology adoption and use	0.009	0.011	-0.010	0.003	0.002	-0.007
	(0.26)	(0.32)	(-0.30)	(0.09)	(0.08)	(-0.28)
Learning capacity of the organisation	-0.056	-0.047	0.019	0.006	0.037	0.038
	(-1.57)	(-1.19)	(0.60)	(0.19)	(1.22)	(1.08)
Education (Ref: secondary education)						
Lower education		-0.004		-0.089***		0.083***
		(-0.17)		(-4.64)		(3.92)
Higher education		-0.017		-0.003		0.014
		(-0.78)		(-0.18)		(0.73)
Tertiary sectors (Ref: secondary sectors)	-0.551	-0.301	1.752***	0.939*	-1.311***	-0.814
	(-1.07)	(-0.56)	(3.45)	(1.87)	(-2.65)	(-1.61)
Geography controls	Yes	Yes	Yes	Yes	Yes	Yes
Years controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.785	1.511	-0.785	3.461*	-0.791	-4.304**
	(0.91)	(0.74)	(-0.46)	(1.92)	(-0.43)	(-2.11)
Observations	496	496	496	496	496	496
R-sq.	0.77	0.80	0.78	0.81	0.77	0.80

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$
Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-2014, 2012-2016, 2014-2018)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table 11. RIT test from basic model

	Share of product innovative enterprises	Share of marketing innovative enterprises
DOWNGRADING		
Digital technology adoption and use	Full mediation	Full mediation
Learning capacity of the organisation	Full mediation	-
MIDDLE CLASS		
Digital technology adoption and use	Full mediation	-
Learning capacity of the organisation	41%	-
UPGRADING		
Digital technology adoption and use	92%	Full mediation
Learning capacity of the organisation	24%	-

Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-2014, 2012-2016, 2014-2018)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Results

We test whether *Digital technology adoption and use* and the *Learning capacity of the organisation* have a direct effect on three indicators of polarisation of the labour market or are rather mediated by the innovation strategies of enterprises.

Our results in Table 10 show that investments in *Digital technology adoption and in* the *Learning capacity of the organisation* do not have any direct effects on the polarisation of the labour market. Indeed, the innovation strategies play a key role of mediation.

In particular, product innovation appears to positively affect the structure of employment. A rise of 1 point in the share of product innovative enterprises in a country-sector cell is correlated with a lower (of 0.18 pp) share of employment in occupations in the first tercile of the wage ranking (downgrading column). By contrast, it is correlated with a higher share of employment in occupations in the third tercile (upgrading column), of 0.09 pp. The share of employment in occupation in the second tercile (middle class column) is also positively correlated with the share of product innovative enterprises, but with non-robust results across different model specifications. Indeed, when we introduce controls for education, the coefficients are no longer significant. Figure 10 syntheses the direct and indirect relationships between inputs of the knowledge production function, innovation outputs and labour market polarisation outcomes.

The RIT test results (Table 11) show that the effect of *Digital technology adoption and use* is fully mediated by the share of product innovative enterprises when considering downgrading and middle class effects. It is also largely mediated when considering upgrading. Product innovation also mediates the effect of the *Learning capacity*, fully mediating it when considering downgrading and partially mediating it when considering middle class effects and upgrading.

The share of product innovative enterprises in a country-sector cell seems thus to have a positive role on the labour market in fostering a sector shift of the structure of occupations towards the upper part of the wage hierarchy.

Process innovation does not appear to influence our polarisation indicators, while organisational innovation has a positive effect only on upgrading. We tested whether organisational innovation has also a mediating role, but the RIT test suggests it is not the case.

Marketing innovation clearly downgrades the labour market by increasing the share of low-paid jobs and, symmetrically, decreasing the share of high-paid ones. Indeed, a rise of 1 pp in the share of marketing innovative enterprises in a country-sector cell is correlated with a higher percentage of employment in occupations in the first tercile, of 0.12 pp (downgrading column). By contrast, it is also associated with a lower percentage of employment in occupations in the third tercile (upgrading column), of 0.11 pp. Marketing innovation play also a mediating role. Results from the RIT test suggest that it fully mediates the effect of *Digital technology adoption and use* on both upgrading and downgrading effects.

Hence, the share of marketing innovative enterprises in a country-sector cell has an opposite effect compared to product innovation strategies, as it fosters a sector shift of the structure of occupations towards the lower part of the wage hierarchy.

The controls for education level that we introduce shows that the share of employees with lower education levels is negatively related with the percentage of employment in middle class occupations, while it is positively related with upgrading. This may suggest that, since 2011, a shift toward occupations in better paid jobs has especially concerned employees with primary level of occupations.

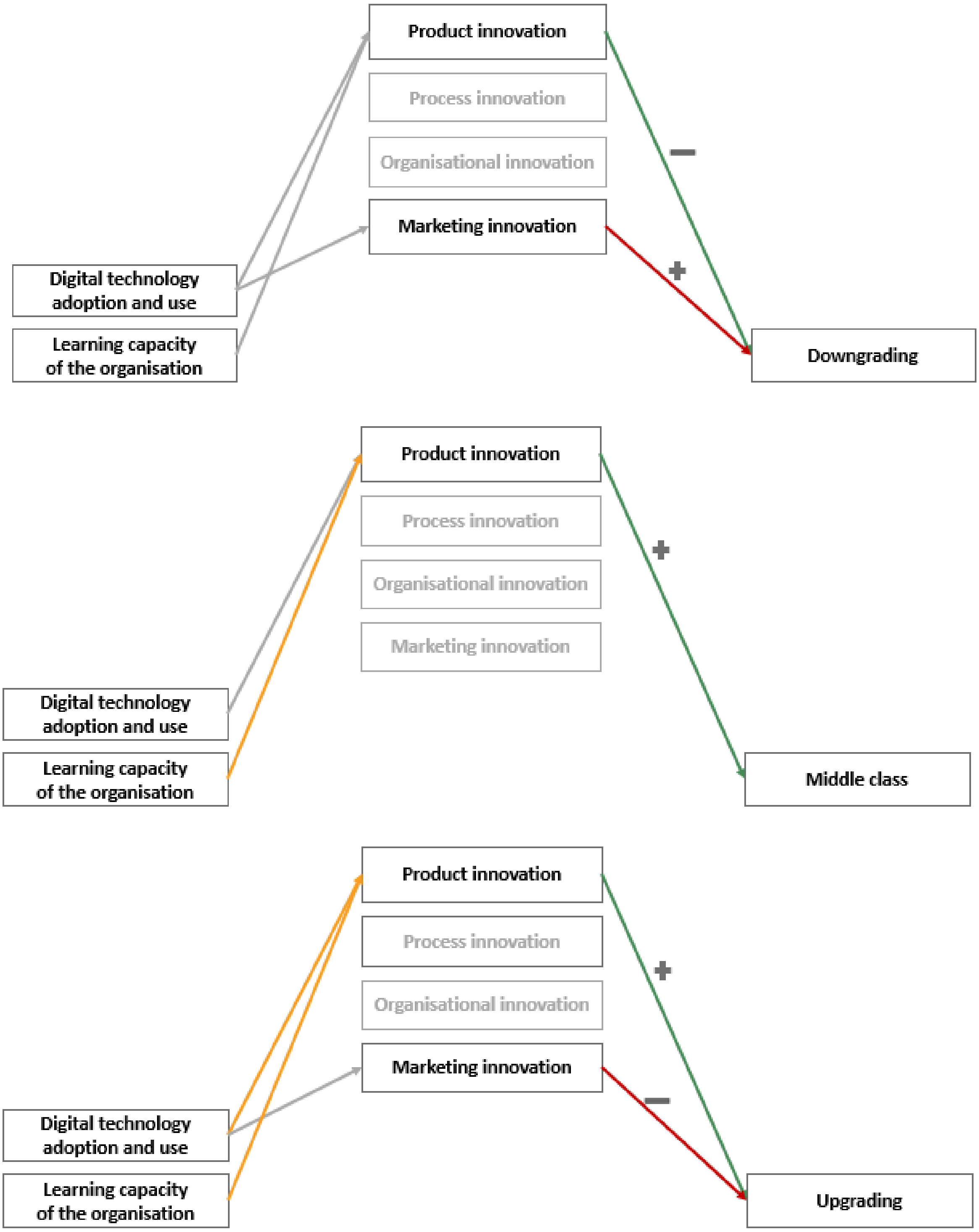
As we are able to compute the polarisation outcomes also at t+3 (2015, 2017, 2019), we tested whether the effect that we observed on t+2 persist when we consider a longer lag of time. Results are reported in Table A9.

We find that the role of innovation strategies remains almost unchanged. In particular, the share of product innovative enterprises has a positive effect in favouring a shift towards occupations in the second and third tercile of the distribution, while reducing employment in occupations in the first tercile. Marketing innovative enterprises have the opposite effect.

Nonetheless, we now find a direct effect of the *Learning capacity of the organisations* in reducing the share of employment in occupations in the first tercile of the distribution. As a consequence, the effect of the *Learning capacity* on downgrading is now only partially mediated by the product innovation strategies, as showed in results from the RIT tests in Table A10, and becomes partially mediated by the marketing innovation strategies of enterprises. Over this longer period, it becomes more evident that, while product innovation reinforce the protective role of the *Learning capacity of the organisations*, marketing innovation reduces - but does not nullify - it.

The effects of *Digital technology adoption and use* on the occupational structure of the workforce remain fully mediated by the share of product and marketing innovative enterprises.

Figure 10: Direct and indirect effects from the SEM



Note: The figure reports only relationships relevant for the analysis of the outcome. A dotted line indicates a direct relationship between inputs and outcomes ("c" type effect), solid lines indicate indirect effects ("a" and "b" type effects). A light grey innovation type box in the middle of the figure indicates no mediation effect. "a" types effects correspond to full mediation when the line is grey, partial when it is orange. "b" type effect leads to a favourable outcome when the line is green, to an unfavourable one when it is red.

4 Conclusions

This report investigates the links between the technological transformation and the labour market outcomes.

As a first step, it describes the technological transformation by mobilising the Beyond 4.0 integrated database CIS-CICT-EWCS. This dataset is a EU-wide cross-country and cross-sector dataset that combines through a “common cell”, which is an industry in a country in a given year, data sources at the employer-level with data sources at the employee level.

This methodology has two key characteristics. First, by gathering information at both the employers’ and the employees’ level, it takes advantage of the richness of having two different and complementary sources of information. Second, as data are aggregated at a meso level, which is the industry within a country, it provides insights from a specific perspective. On the one hand, it allows taking into account those differences due to the market structure, the policy drivers and the macroeconomic patterns that shape the technological transformation, which are usually overviewed when just looking at a macro level. On the other hand, it allows taking into account reallocation and selection effects across firms within the same sector, which cannot be assessed focusing on individual-level data.

Inspired by the knowledge production function in the CDM model (Crépon et al., 1998), we describe the technological transformation in the digital age as the relationship between different innovation inputs able to increase the stock of knowledge within companies and innovation outputs. On the input side, we consider the role of R&D and we develop a synthetic indicator of *Digital technologies adoption and use* that takes into account the heterogeneity of ICTs and digital technologies and their constant renewal. Then, we add a new argument, the *Learning capacity of the organisation*, which proves to be a distinct and impactful dimension of the knowledge production function. The *Learning capacity* captures the adoption of management tools and organisational practices concerned with the improvement of individual and organisational learning. On the output side, we consider an extended measure of innovation that includes technological innovation (product and process innovation) and non-technological innovations (organisational and marketing innovation) as well as their combinations to account for more complex forms of outputs from innovative activities in the digital age.

We then move towards the analysis of the nexus between the technological transformation and labour market outcomes. We step into the debate about the fear of massive skills and job destruction due to automation, robotics and AI in the current digital revolution. Emerging digital technologies seem to affect workers in all industries and across different occupational ranks. Nevertheless, each technological revolution also generates new goods and services, which by raising demand, create new jobs that use new skills.

We focus on two specific outcomes. The first one is the unemployment rate at the country-sector level, which thus refers to the job loss of people who were employed in a specific sector, but who, despite being available for work and having taken specific steps to find a job, have not been recruited in their former sector or in another one. The second one refers to indicators of polarisation that accounts for the change in the share of employment at the sector-country level for occupations belonging to the first, second or third terciles of a wage ranking distribution with respect to a base year (2011).

Our results show that investing in the *Learning capacity of the organisation* and in *Digital technologies* stimulates innovativeness in enterprises. All types of innovation are favoured as well as all types of firm-level combinations of innovation except technological innovations only for the *Learning capacity* and non-technological innovations only for *Digital technologies adoption and use*.

However, these two types of investments influence on labour market outcomes differently. The effect of investments in *Digital technology adoption and use* are fully mediated by innovation while mediation is either partial or nil for investments in the *Learning capacity of the organisation*. In particular, this latter investment provides direct protection against unemployment and, in the longer run against occupational downgrading.

This result aside, innovation plays an important role in determining the labour market outcomes of technological transformation. We find that, depending on its characteristics, innovation can be either beneficial or detrimental to employees.

Product innovation is for the good as it mediates positively the relationship between the *Learning capacity* and *Digital technologies* and labour market outcomes. Higher levels investments are related with less unemployment and occupational downgrading and more occupational upgrading. This result suggests the dominance of a market expansion effect in sectors where a larger share of firms introduce goods or services that are new or significantly improved with respect to their characteristics or intended uses.

Marketing innovation is for the bad as its mediation effect on labour market outcomes is opposite. However, it mainly concerns *Digital technologies adoption and use*. For the *Learning capacity of the organisation* we only find no mediation for outcomes at t+2 and a partial mediation between 28% and 40% for changes in the occupational structure at t+3. This result suggests the predominance of a business stealing effect in the sectors of companies that introduce significant changes in product design, packaging, placement, promotion or pricing to the detriment of employees in companies that do not.

Overall, we find two main results. First investing into the *Learning capacity of the organisation* appears as a win-win strategy leading to more innovativeness and improved labour market outcomes. Second, even though labour market outcomes depend on the relative shares of product and marketing innovations, the technological transformation over the second decade of the millennium is not associated with increased polarisation. In sectors where investments in *Digital technologies* and *Learning capacity* lead to a share of product innovative firms which is larger than that of marketing innovative firms, unemployment rates are lower and the job structure shifts upward in the wage ranking. On the contrary, when marketing innovation dominates, sector level unemployment develops and low paid jobs grow to the detriment of the best paid ones.

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6 Appendix

Table A1: Surveys' coverage and common cells

Survey	Editions/years	Country coverage	Sectoral coverage
Community survey on ICT usage and e-commerce in enterprises (aggregated data, Eurostat)	2010 - 2016	EU-27, UK, Norway, Serbia, Turkey, Iceland, North Macedonia.	NACE Rev. 2 sections C to N, plus S, at 1-digit level. Sub-aggregates are available for section C (C10-12, C10-18, C10-33, C13-15, C16-18, C19-22, C19-23, C23-25, C24-25, C26, C26-33, C27-28, C29-30, C31-33), G (G45, 46 and 47); J (I55 and 56; J58-69, J61, J62-63); and K (K64, 65 and 66). From 2014, the financial sector (K) is not covered anymore. Data about sectors D and E are provided only coupled. For some sectors (section C, G, I, J), data are finer grained in sub-aggregates.
Community Innovation Survey (aggregated data, Eurostat)	2010, 2012, 2014, 2016	EU 27, UK, Norway, Serbia, Turkey, Iceland, Switzerland, North Macedonia and, from 2016, Montenegro	NACE Rev. 2 sections A to N, 2-digit level
European Working Condition Survey (Eurofound)	2010, 2015	EU27, UK, Albania, North North Macedonia, Montenegro, Serbia, Turkey, Norway and Switzerland	NACE Rev. 2 all sections, 2-digit level

Note: The common coverage among the three dataset is of 32 countries (the 28 Member States plus North Macedonia, Norway, Serbia, Turkey and the UK); 11 sectors (the NACE Rev. 2 at 1-digit level, sections C to N, but with sections D and E aggregated), and 3 time periods (2010-2012, 2012-2014, 2014-2016).

Table A2: Summary statistics of selected variables

Variable	Number of observations	Mean	Std. Dev.	Min	Max
Share of product innovative enterprises	715	21.07	13.25	0.20	66.10
Share of process innovative enterprises	718	22.20	11.35	1.50	75.65
Share of organisation innovative enterprises	718	27.02	12.10	0.00	66.65
Share of marketing innovative enterprises	718	22.91	11.61	0.00	61.55
Share of product and/or process innovative enterprises	687	35.24	16.83	1.55	80.30
Share of product and/or process innovative enterprises only	709	10.31	6.13	0.00	34.70
Share of organisation and/or marketing innovative enterprises	721	34.69	14.00	0.00	73.60
Share of organisation and/or marketing innovative enterprises only	712	12.36	5.48	0.00	29.70
Share of product and/or process AND organisation and/or marketing innovative enterprises	697	21.64	11.85	0.00	67.95
R&D exp. per employee (ln, th. euro)	651	2.00	3.49	0.00	23.10
Digital technology adoption and use	947	46.39	16.54	0.41	95.22
Learning capacity of the organisation	981	55.72	9.09	29.62	88.89
Enterprise size	708	85.42	77.31	13.96	1012.61
Share of enterprises receiving public funding	613	23.11	14.66	0.00	65.00
Share of enterprises engaged in cooperation for innovation activities	712	35.39	16.44	0.00	82.50

Source: Beyond 4.0 integrated database CIS-CICT-EWCS (2010, 2012 and 2014)
Coverage: EU27 plus North Macedonia, Norway, Serbia, Turkey and the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table A3: Digital technology adoption and use: summary statistics

Variable	Number of observations	Mean	Std. Dev.	Min	Max
Digital technology adoption and use synthetic indicator	*947*	*46.39*	*16.54*	*0.41*	*95.22*
E-commerce	842	27.55	15.55	0	74.86
Connection	907	71.74	16.62	4.68	100
Web and social media	925	43.61	16.35	0	92.44
E-business	897	24.93	13.67	1.50	76.00
Cloud computing	867	13.52	14.88	1.55	89.46

Source: Beyond 4.0 integrated database CIS-CICT-EWCS (2010, 2012 and 2014)
Coverage: EU27 plus North Macedonia, Norway, Serbia, Turkey and the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table A4: List of countries by geographical groups

NORTHERN EUROPE	WESTERN EUROPE	CENTRAL AND EASTERN EUROPE	SOUTHERN EUROPE
Denmark Estonia Finland Lithuania Latvia Norway Sweden	Austria Belgium Germany France Ireland Luxembourg Netherlands United Kingdom	Bulgaria Czech Republic Croatia Hungary Poland Romania Serbia Slovenia Slovakia North Macedonia	Cyprus Greece Spain Italy Malta Portugal Turkey

Table A5: Learning capacity indicator sub-dimensions: summary statistics

Variable	Number of observations	Mean	Std. Dev.	Min	Max
Learning capacity of the organisation composite indicator	*656*	*55.75*	*9.43*	*29.62*	*88.89*
Cognitive dimension of work	656	72.56	14.59	11.37	100
Training opportunities	656	40.17	17.66	0	100
Autonomy	656	61.75	15.01	16.11	100
Motivation	656	60.84	16.37	0	100
Autonomous teamwork	656	25.64	13.34	0	80.91
Direct help and support	656	69.74	14.62	14.99	100
Supportive supervisory style	656	79.37	9.99	35.53	100
Participation	656	38.10	13.20	5.05	86.01

Source: Beyond 4.0 integrated database CIS-CICT-EWCS, 2010 and 2015
Coverage: EU27 plus North Macedonia, Norway, Serbia, Turkey and the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table A6: WLS about the inputs-outputs relationship, with robust standard errors and number of employees as weights

	Share of Product innovative enterprises	Share of Process innovative enterprises	Share of Organisation innovative enterprises	Share of Marketing innovative enterprises
R&D exp per employee	2.696^{***}	1.824^{***}	1.462^{***}	1.691^{***}
(ln, th. euro)	(11.39)	(7.96)	(7.08)	(7.76)
Digital technology	0.255^{***}	0.071^{*}	0.075^{*}	0.175^{***}
adoption and use	(5.10)	(1.65)	(1.76)	(3.97)
Learning capacity	0.127^{**}	0.102^{**}	0.260^{***}	0.083^{*}
of the organisation	(2.44)	(1.98)	(5.52)	(1.69)
Tertiary sectors (Ref:	1.955^{**}	-2.803^{***}	1.490^{*}	4.622^{***}
secondary sectors)	(2.00)	(-2.89)	(1.80)	(5.14)
Time dummies	Yes	Yes	Yes	Yes
Geographical groups dummies	Yes	Yes	Yes	Yes
Constant	2.944	20.05^{***}	10.57^{***}	8.889^{***}
	(0.80)	(5.93)	(3.33)	(2.68)
Observations	552	555	555	555
Adjusted R^2	0.453	0.302	0.546	0.327

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$
Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-2014, 2012-2016, 2014-2018)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table A7. Structural Equation Model about technological transformation and unemployment rates at the country-sector level at t+3

	Unemployment rates	
Share of product innovative enterprises	-0.067***	-0.089***
	(-3.15)	(-4.68)
Share of process innovative enterprises	-0.001	-0.001
	(-0.03)	(-0.03)
Share of organisation innovative enterprises	-0.010	-0.014
	(-0.51)	(-0.72)
Share of marketing innovative enterprises	0.072***	0.101***
	(2.78)	(4.30)
Digital technology adoption and use	-0.012	-0.018
	(-1.00)	(-1.51)
Learning capacity of the organisation	-10.59***	-14.90***
	(-5.72)	(-7.54)
Education (Ref: secondary education)		
Lower education		0.020
		(1.11)
Higher education		0.047***
		(4.27)
Tertiary sector (ref: secondary sectors)	-0.891**	-1.547***
	(-2.53)	(-4.01)
Geographical groups of countries	Yes	Yes
Time dummies	Yes	Yes
Constant	15.72***	16.37***
	(12.48)	(13.99)
Observations	*548*	*548*
R-sq.	*.85*	*.87*

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$
Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-15, 2012-17 and 2014-19)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table A8. RIT test from basic model at t+3

	Share of product innovative enterprises	Share of marketing innovative enterprises
UNEMPLOYMENT		
Digital technology adoption and use	Full mediation	Full mediation
Learning capacity of the organisation	7%	-

Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-15, 2012-17 and 2014-19)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table A9. Technological transformation and polarisation at t+3, SEM results

	Downgrading		Middle class		Upgrading	
Share of product innovative enterprises	-0.252***	-0.246***	0.168***	0.134***	0.076	0.101**
	(-5.73)	(-5.50)	(3.69)	(3.03)	(1.54)	(2.11)
Share of process innovative enterprises	0.039	0.037	-0.024	-0.019	-0.021	-0.025
	(1.03)	(1.03)	(-0.66)	(-0.58)	(-0.46)	(-0.61)
Share of organisation innovative enterprises	-0.040	-0.040	-0.001	-0.012	0.053	0.057*
	(-1.05)	(-1.06)	(-0.02)	(-0.37)	(1.50)	(1.76)
Share of marketing innovative enterprises	0.181***	0.179***	-0.090**	-0.085**	-0.093**	-0.095***
	(4.48)	(4.44)	(-2.39)	(-2.40)	(-2.42)	(-2.69)
Digital technology adoption and use	0.001	0.001	-0.031	-0.013	0.029	0.017
	(0.02)	(0.04)	(-0.88)	(-0.38)	(1.01)	(0.60)
Learning capacity of the organisation	-0.084**	-0.088**	0.033	0.049	0.043	0.041
	(-2.17)	(-2.12)	(1.03)	(1.30)	(1.29)	(1.10)
Education (Ref: secondary education)						
Lower education		0.004		-0.108***		0.090***
		(0.19)		(-5.33)		(3.98)
Higher education		-0.001		-0.028		0.020
		(-0.04)		(-1.35)		(0.96)
Tertiary sectors (Ref: secondary sectors)	-1.026*	-0.925	1.807***	1.135**	-0.968*	-0.507
	(-1.85)	(-1.64)	(3.16)	(2.20)	(-1.66)	(-0.93)
Geography controls	Yes	Yes	Yes	Yes	Yes	Yes
Years controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.146*	3.036	-0.644	3.153	-1.713	-5.288**
	(1.68)	(1.53)	(-0.32)	(1.45)	(-0.86)	(-2.47)
Observations	468	468	468	468	468	468
R-sq.	0.78	0.80	0.77	0.77	0.77	0.80

t statistics in parentheses;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$
Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-15, 2012-17 and 2014-19)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

Table A10. RIT test from basic model at t+3

	Share of product innovative enterprises	Share of marketing innovative enterprises
DOWNGRADING		
Digital technology adoption and use	Full mediation	Full mediation
Learning capacity of the organisation	31%	30%
MIDDLE CLASS		
Digital technology adoption and use	Full mediation	Full mediation
Learning capacity of the organisation	Full mediation	40%
UPGRADING		
Digital technology adoption and use	-	Full mediation
Learning capacity of the organisation	-	28%

Source: Beyond 4.0 integrated database CIS-CICT-EWCS-LFS (2010-15, 2012-17 and 2014-19)
Coverage: EU27 (Sweden excluded) plus the UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C to N, D-E aggregated.

BEYOND 4.0

PART B - TASK 5.2
STRUCTURAL CHANGE OF OCCUPATIONS, TASKS AND SKILLS

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Deliverable type version: D5.1 – May 2023
Associated Work Package: WP5
Lead: CNAM-CEET
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European Commission

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 822296.

Document Summary

Document type:	*Deliverable 5.1 – Part B*
Title:	*Structural change of occupations, tasks, and skills*
Author/s:	*Mathias Cuypers and Clara R. Behrend*
Reviewer/s:	*Steven Dhondt, Nathalie Greenan, Silvia Napolitano*
Date:	*April 2023*
Document status:	*Final*

Abstract

This report investigates effects of the usage of digital technologies as well as the learning capacity of organisations on tasks, skills and the occupational structure. Using an aggregated data (the Beyond 4.0 dataset) it was found that high levels of both factors seem to favour an increase in task and duties, a lower match of tasks and skills and more occupational restructuring. However, the simultaneous occurrence of both factors, seems to have some mitigating effects on the proportion of over-skilled employees and the extent of change in the occupational structure. Looking at the effects of changes of these factors, increases in the learning capacity are related to an increase of under-skilled employees, while an increase of digital technology usage induces an increase in the share of over-skilled employees.

Acknowledgements

We would like to thank Sally Wright and Sudipa Sarkar for their valuable contributions to the finalisation of this paper.

For this paper, the following consulting/analysis services of the Statistical Consulting and Analysis (SBAZ) department of the Centre for Higher Education at TU Dortmund University were used: statistical methodology, data evaluation.

Content

Executive Summary

This report investigates the links between digital technologies and the learning capacity of the organisation as inputs of the technological transformation on the one hand and changes in tasks, match between tasks and skills, and occupational restructuring on the other.

The basic theory-based expectation is that working in environments affected by technological change brings challenging aspects to the structuring of work. Namely, it is expected that employees will be confronted with new or different tasks and duties and that this change may also mean that one's skills might no longer fully match the new task requirements. This is also likely to lead to a change in the occupational composition of workforces. Investments into the learning capacity of the organisation through the adoption of a specific set of organisational practices can bring similar effects on work structures as technological changes. However, it is also expected that in certain situations an increased learning capacity can also help to mitigate some of the described outcomes.

The BEYOND 4.0 dataset is used to test the hypotheses of this paper. Here, variables from several European survey data sources are combined at the sectoral level in countries, where the individual values represent shares or scores within these country-sector cells. For the question about tasks and the match between tasks and skills, items from the European Working Conditions Survey (EWCS) are used. Data from the European Labour Force Survey (EU-LFS) is used for the change in occupational structure. The adoption and use of digital technologies is approached through the Community survey on ICT usage and e-commerce in enterprises. The learning capacity of the organisation is operationalised using eight dimensions measured with employee level responses to the EWCS.

The results only partially confirmed the hypotheses. A high digital technology status and a high learning capacity tend to be related similarly with the outcomes: increase in tasks and duties, higher share of employees needing further training (under-skilled), lower share of employees able to perform more demanding duties (over-skilled) and more occupational restructuring. However, digital technology effects are less robust that learning capacity ones. In more complete models, high digital technology status is mostly related with a lower share of over-skilled employees and more occupational restructuring when the relationships with high learning capacity status remain significant. However, when both statutes are high, estimates of interaction effects show that there is less occupational restructuring and a higher proportion of employees that are over-skilled. Things seems to suggest that in companies with a high innovative capacity, the technological transformation was putting less pressure on human resources. When we further look at the relationship between changes in inputs and changes in outcomes, the two inputs behave differently: an increase in digital technology adoption and use is related with an increase in tasks and duties performed, a decrease in the share of employees whose skills match their duties and an increase in the share of over-skilled employees. An increase in the learning capacity of organisations is related with an increase of under-skilled employees.

Some restrictions in the EU-wide data released for scientific purposes put strong limitations in the data combination strategy. In particular, we have not been able to consider the skills needs and skills gaps perceived by employers, the within sector heterogeneity, emerging digital technologies like artificial intelligence or to go further than a descriptive analysis.

1. Introduction

This report investigates the structural transformation of occupations, tasks and skills and its relation to the technological transformation. It summarises the work done in the BEYOND 4.0 project's task 5.2. For that, data from the BEYOND 4.0 database is used. This database aggregates and links different European surveys providing data on technology use in enterprises, employment, qualification, occupational structure, organisational characteristics, innovation activity and skill match on employer and employee levels and for several points in time[1]. In the following, the context of our research topics is first discussed (1.1), before the connections to the research framework of WP3 (1.2) as well as the structure of the report (1.3) are outlined.

1.1 Context

The way digital transformation changes skill requirements, task-content of jobs and occupational structure has been the subject of scientific debate in the social sciences and economics. Several arguments found in the literature are important for the research presented in this report. The idea that automation leads to the loss of jobs while increasing productivity is one of the most frequently discussed issues related to technological transformation found in the literature. One of the most prominent works using this idea is Frey and Osborne's (2013) study on the future of employment and the computerisation of jobs. Based on the assumption that the composition of tasks within occupations remained the same over time, they identified tasks within occupations with a high risk of automation to predict which occupations were at high risk of automation. The chosen comparison **between jobs and between occupations** is a much-used perspective to illustrate – not only technologically induced – labour market developments, e.g. when creating forecasts for the occupational structure (e.g. Atkinson & Wu, 2017; Cedefop, 2018; Eurofound, 2015b).

Other scholars, some of whom are critical of the approach taken by Frey and Osborne, focus on changes **within jobs and occupations** (Arntz et al., 2016; Autor et al., 2003; Dengler & Matthes, 2015). An alternative assumption, for example, is that automation does not directly affect entire jobs but specific tasks within jobs and that jobs might often adapt to new tasks rather than disappear altogether. In such situations, it seems necessary to analyse changes in the composition of tasks within jobs and occupations. That is, not only the disappearance of tasks but also the emergence of new tasks.

The analysis of tasks is related to the analysis of skills. The composition of tasks within a job also defines the skill and qualification requirements.

However, looking only at the shifts in tasks gives a partial picture of the impact of digital transformation. With the variety of skills needed and skills employees have, it is not possible to conclude from the datasets at hand how challenging the digital transformation is for all involved parties. From the employers' perspective, it is crucial to understand how these changes affect the match between employees' skills and the skills required to do the jobs. This skill match changes with digital transformation. Different arguments seem plausible in this context. Where tasks are automated, the remaining tasks can be the more complex ones and require higher skill levels or

[1] The methodology and data are described in chapter 3 "Methodology"

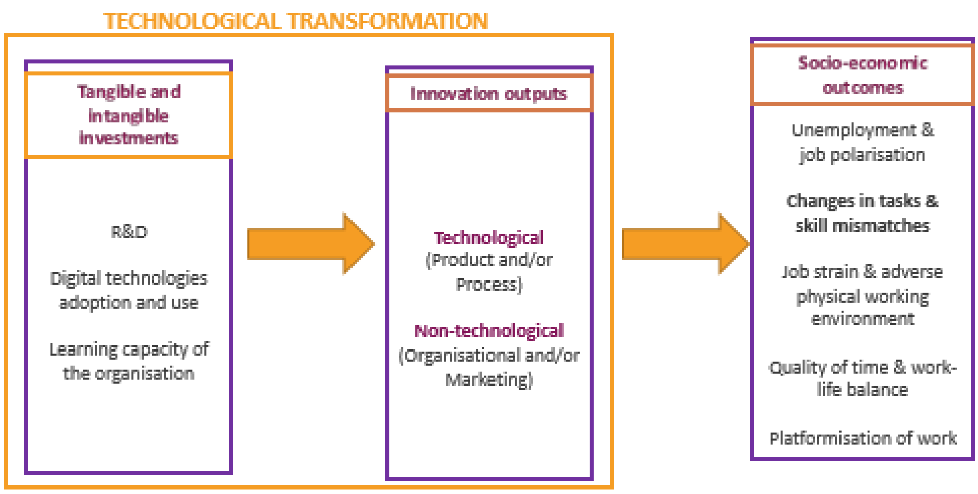
different types of skills from the employees (the skill-biased technological change thesis). This can then lead to a situation of an under-skilled workforce. Also, where tasks of medium or high-skilled job profiles are being automated or facilitated by new technology, the skills of employees might become economically obsolete and the employees could then find themselves over-skilled (compare also for example with Palmer, 2017, table 1, p. 11; or in Beyond 4.0 Deliverable 2.1, Warhurst et al., 2019, pp. 34–35).

In economics and social innovation research, it has been argued that the effect of technology use in an organisation is always facilitated and influenced by factors other than the technology and its technical implementation alone (Bijker et al., 2012; Dhondt et al., 2021; Kohlgrüber & Schröder, 2019; Kopp et al., 2019). Indeed, work design theorists have argued that the strategic decisions made within organisations are the main factor that determines the task compositions of job profiles and the skill requirement changes that occur accordingly (Greenan et al., 2022; Greenan & Napolitano, 2021; Lam, 2005; Lam & Lundvall, 2006). This logic is then also applied to strategic decisions about technology. Therefore, the three domains of technology, organisation and skills are seen as interdependent (Greenan, 2003).

1.2 Research model

Following this logic, the conceptual framework of BEYOND 4.0, WP3 and WP5 outline that the organisational characteristics most influential and feasible to measure with existing datasets are innovation, technology adoption and use, organisational structure and organisation of work (Greenan et al., 2023). The components of this framework are understood as part of an innovation process, where some of them are understood as inputs, and some as (innovation) outputs (Greenan et al., 2023; Greenan and Napolitano, 2023). In this approach to the measurement framework, the topic of this report is regarded as a socio-economic outcome (see Figure 1).

Figure 1 The approach to the measurement framework (Greenan et al., 2023)



One important component on the input side, which draws attention to the important role of organisational strategies and policies in managing technological change, is the organisational learning capacity (see also Greenan and Napolitano, 2023). It has been defined as “the capability of an organization to process knowledge—in other words, to create, acquire, transfer, and integrate knowledge, and to modify its behaviour to reflect the new cognitive situation, with a view to improving its performance” (Jerez-Gómez et al., 2005, p. 716). The learning capacity of an organisation is its ability to adapt and compete at low cost through learning (see Lorenz & Greenan, 2010). It is related to the skills, management tools and organisational practices that support employees with their learning as well as organisational learning through an organised setting in which knowledge is also shared and distributed among members (ibid.). An organisation that invests heavily in learning capacity is a learning organisation (ibid.). It promotes innovative work behaviour of employees that stimulates innovation without directly consuming scarce environmental resources. Within the measurement framework (Figure 1), the learning capacity of the organisation is regarded as an input of the innovation process.

These company-level characteristics and decisions, captured in this analysis by the indicator of learning capacity of the organisation, are also embedded in public policy frameworks of laws and regulations that differ between countries. Public policies also have direct influences on the outcomes under investigation, for example, through education and labour market policy. In addition, the overall social and economic policies also play a role. Following this line of argument, the historical analysis of technological revolutions by Perez and Leach (2022) clearly shows state policies' role in shaping the technological revolution's economic and social outcomes. One of the institutional theories commonly used to understand transnational differences in public policy systems is the typology of welfare regimes (Esping-Andersen, 1990), whose geographical coverage has been extended in the course of time. For this reason, we prefer it to other typologies that are more specific to the subject matter of this chapter, such as the typology of skill formation systems (Busemeyer & Trampusch, 2011).

1.3 Structure and outline of the report

Having outlined the background context, this paper investigates whether, and if so, how digital technology adoption and use and organisational learning capacity affect the increase and decrease of tasks for employees, the development of match (or mismatch) between employee’ skills and the skill requirements of jobs, as well as the overall structure of occupations. In doing this, the analysis considers both changes between occupations (occupational structure) as well as the developments within occupations (task & skills).

From this theoretical background, the research questions that were derived are set out in chapter 2, before the methodology is explained in chapter 3. Chapter 4 contains the results of the statistical analysis and Chapter 5 the main conclusions.

2. Hypotheses

This chapter translates the main research questions into a set of researchable hypotheses.

2.1 Tasks increase and decrease

Following on from this theoretical derivation and as also laid out in more detail in Deliverables 2.1 (Warhurst et al., 2019) and 6.1 (Behrend et al., 2022), the dissemination of new technologies has led to and will continue to influence the composition of tasks within jobs. The literature discusses the elimination of tasks, the addition of new tasks, and changes in tasks within jobs. Changes in task profiles can lead to employees reporting an increase or decrease in the number of their tasks.

H1.1 Employees working in environments that are affected by high technology use or an increase in technology use are more likely to experience an increase in the number of their tasks.

2.2 Skill match and mismatch

Changes in tasks lead to changes in the skill requirements of jobs and may subsequently lead to a mismatch between the skills of the job holder and the required skills necessary to perform jobs. This is conceivable in two directions: On the one hand, workers may lack skills for new tasks so that they are under-skilled; on the other hand, they may have skills that they can no longer use, such as when old tasks are automated or replaced with new ones. If so, it means that employees become over-skilled.

H2.1 Employees working in environments affected by high technology use or an increase in technology use are more likely to experience a mismatch between their own skills and the skills required to do their jobs.

2.3 Structure of occupations

One widely discussed (potential) effect of technological transformation is a change in the occupational structure. The reasons given in the explanation of such change vary in different strands of the literature, ranging from down-skilling and up-skilling through to automation of jobs to changes in jobs and task constellations within the companies that are adopting new technology.

While we expect that the largest degree of change will be observed within occupations, we also expect that some change to the occupational structure may be apparent, such as a change in the share of groups of occupations.

H3.1 Working environments that are affected by technological change are more likely to result in a change in the occupational structure.

2.4 Organisational practices/learning capacity

When it comes to organisational practices, we expect the learning capacity of an organisation to play a favourable role (see section 1.2). Similarly to digital technologies, companies also invest in their learning capacity to generate innovations - both are part of the input side of the innovation process (see section 1.2). Building the learning capacity of an organisation is skill demanding as it rests in particular on the preservation of the cognitive dimension of work, on workers' autonomy in cognitive tasks and on autonomous teamwork. Therefore, we generally expect that a higher or increasing learning capacity will imply, like higher or increased usage of digital technologies, more tasks, a higher skill mismatch and a changed job structure.

We therefore expect:

H4.1 In sectors with a higher or growing learning capacity, employees are more likely to experience an increase in the number of their tasks.

H4.2 In sectors with a higher or growing learning capacity, the mismatch of skills and tasks of their employees is higher or growing.

H4.3 In sectors with a higher or growing learning capacity, the change of the occupational structure is higher or growing.

But what happens in sectors that have invested heavily in both learning capacity and digital technologies? Such sectors should be at the spearhead in terms of their innovative capacity. Are the effects on tasks, skills (mis-)match and job structures also found here, or can differences be found? Our assumption is that these sectors are better able to manage the technological transformation than other sectors, so that these effects are mitigated.

We therefore expect:

H4.4 In sectors with a higher or growing learning capacity in combination with a higher or growing uptake of digital technologies, effects of each on the number of tasks, the (mis-)match of tasks and skills as well as the occupational structure will be either mitigated or reversed.

3. Methodology

3.1 The BEYOND 4.0 dataset

The BEYOND 4.0 datasets, created within WP3, combine data from different surveys and form the basis for our analysis. Each of the individual data sources was based on surveys that had their independent samples. Therefore, the data was matched at the lowest possible common aggregated level. For the aggregation of the data, sectors (according to the NACE rev. 2 classification) and countries (NUTS 0) served as the common matching points so that we were able to analyse sector-country cells, i.e. sectors within countries. Three different datasets have been combined with different surveys and time coverage. For the purpose of this study we use the Beyond 4.0 integrated database CIS-CICT-ECWS-LFS covering 2010-2016 (for details on the construction of the dataset, see Greenan et al., 2023).

For the operationalisation of our key concepts, we focus on information coming from the Community ICT usage by enterprises survey, the European Working Conditions Survey and the EU Labour force survey for the year groups 2010/2011 and 2014/2015 (see section 3.2). For analytical purposes, data from all sources and both points in the time needed to be available, so only cases including all sources and points in time were retained: While the aggregated dataset included 746 sector-country cells, the final number of sector-country cells had to be reduced in this analysis.

The EU-LFS had 584 valid cases for both points in time, the EWCS had 554 cases for both points in time, and the technology indicator, which was based on Eurostat data on ICT usage in companies, was available in 310 country sector-cells, making the latter a particular bottleneck. In the end, a total of 256 cases were retained for this analysis. These cases cover 29 countries (EU-27 plus UK and Norway) and 10 sectors (NACE Rev. 2 1-digit sectors C, F to N).

3.2 Operationalisation of key concepts

The operationalisation of key concepts was drawn from three data sources that were integrated into the BEYOND 4.0 database (EU-LFS, the EWCS and the ICT usage in enterprises). Based on the available data and survey edition years, the decision was made to focus on two time points. The first point in time (**t_0**) relates to data from 2010 or 2011. The second point in time (**t_1**) relates to data from 2014 or 2015. Data from the EWCS was from the years 2010 and 2015, data from the EU-LFS was from the years 2011 and 2015, and data from the ICT Usage in Enterprises Survey was from the years 2010 and 2014.

Taking into account the analysis of the state of the art of research (see chapter 1 Introduction) and theoretical definitions developed as part of Work Package 3 (Greenan et al., 2023), Deliverable 6.1 (Behrend et al., 2022), and Deliverable 2.1 (Warhurst et al., 2019), the concepts relevant to operationalisation in this working paper are discussed below.

The main variables for testing the hypotheses include the technological transformation, the task composition of work, the resulting skill requirements, the occupational structure, and the role of organisational practices, public policies and socio-demographic/economic aspects. For each individual concept, unless reported otherwise, three variables were used: One **variable for t_0** (range of values 0 to 1), one variable for **t_1** (range of values 0 to 1) and one **change variable** (Δt_{01}), which was in each case calculated by subtracting the values of t0 from the values of t1 (range of values -1 to 1). Each of the variables is now explained.

Technology indicator

How can “working environments affected by technological change” be identified within the combined dataset? Generally, the current technological transformation refers to the broad take-up and implementation of new digital technologies by employers (companies, public service organisations and others). These technologies include new generations in production processes and the supply chain, integrated use of cloud services for a centralised and digital office administration, various kinds of robotics, advanced automated data analysis including deep learning and similar types of artificial intelligence (AI), technology automating predictive maintenance, assisting digital technologies such as pick-by-voice, virtual reality, and others. However, existing European surveys currently measure the usage of only some of these technologies.

The data on technological change can be explored at the employer level using the Community Survey on **ICT usage by enterprises**. This survey collects data on different types of technology used in enterprises, including internet access, mobile broadband internet access (3G), cloud computing (CC) services, use of social networks, enterprise runs a website, customer relation management software, ERP software package to share information between different departments, online purchasing, and e-commerce sales. Each specific technology indicator in the BEYOND 4.0 dataset represents the proportion of companies using these technologies in the sector-country cells. We calculate a Digital technology adoption and use indicator taking into account both the use and the novelty of the technology: the percentage of enterprises that use the technology in a given industry within a country is weighted using the inverse of the European diffusion rate for each technology in 2010, which proxies its technological intensity. In doing so, those technologies that are reaching their exhaustion point have lower weights, while emerging technologies have higher ones. This overall indicator is then standardised leading to a range from 0 to 1 (see Greenan et al., 2023). In addition, for a descriptive analysis, the values of the indicator (respectively of its change over 2010-2014) were used to divide the cases of the database into quartiles, so that the cases with the highest technological status (respectively the highest technological change) were in the fourth quartile.

In accordance with the hypotheses, work environments are understood as affected by digital technologies in two ways. Firstly, when looking at the change variable, high values represent sectors where the difference in Digital technology adoption and use indices between t_1 and t_0 is particularly high (technologically changing sectors). Secondly, the t_1 and t_0 variables identify sectors in which the Digital technology standard is particularly high (technologically strong sectors).

Task increase and decrease

Several items in the EWCS focus on the proportion of working time that certain tasks take up. However, our focus lies on a general question that captures the overall change in the number of tasks within the last twelve months (see Table A9). This indicator is coded as dummy variables and represents proportions in the country-sector cells.

Skill match and mismatch

Skills (mis-)match is conceptualised as those employees who report needing further training to cope with their duties (under-skilled), those where their present skills correspond well with their duties (skill match), and those who have the skills to cope with more demanding duties (over-skilled), calculated in the respective country-sector cells. The item is based on a single question from the EWCS (see Table A10). The three codes represent the proportions of respondents who selected the respective answer option in the country-sector cells.

Structure of occupations

For our purposes, the BEYOND 4.0 combined database includes an indicator for the proportions of different occupational groups in country-sector-combinations according to the ten major groups of the ISCO-08 classification (see International Labour Office, 2012, p. 65). The ISCO classification structures occupations by processing information on skills, measured by task and duties, information on formal education (by ISCED-97) as well as experience and informal on-the-job training (International Labour Office, 2012, p. 11). The ten major groups are:

1. Managers
2. Professionals
3. Technicians and associate professionals
4. Clerical support workers
5. Service and sales workers
6. Skilled agricultural, forestry and fishery workers
7. Craft and related trades workers
8. Plant and machine operators, and assemblers

9. Elementary occupations
10. Armed forces occupations

In contrast to the other constructed variables, only the changes of proportions of the occupational groups in the cells between t_1 and t_0 were analysed, not the proportions at the two points in time t_1 and t_0. This was done as the change of the occupational structure was of interest and not the different occupational structures of sectors per se (see chapter 2).

An indicator was also created to represent the overall change in the structure of occupations. It is the sum of all absolute values of change of proportion in each ISCO categories when subtracting t_1 from t_0 values. This **overall change of ISCO categories** indicators takes a range of values from 0 to 10.

Organisational practices/learning capacity

When examining the relation between technological change and the three named factors (tasks/proportions of occupations and level of educations/skills mismatch), it is important to integrate the role of **organisational practices** into the modelling. The hypothesis is that these practices within organisations moderate how technological change affects the change of tasks, the share of certain occupations, as well as the degree of skills mismatch. The indicator of the learning capacity of organisation is used to measure these organisational practices (see definition in 1.2).

We used the organisational Learning Capacity index developed to estimate organisations' capacity to innovate through its workforce. It is constructed at the individual level as the sum of eight sub-dimensions from items in the EWCS data: the cognitive dimension of work, training opportunities, autonomy, motivation, autonomous teamwork, direct help and support, supportive supervisory style, as well as participation. The sub-dimensions were normalised so that each dimension had the same weight in the final indicator. The final composite indicator has been normalised to simplify its interpretation so that the values range from 0 (absence of learning capacity) to 1 (maximum capacity) (Greenan et al., 2023).

Public policy

The role of **public policy** was considered adding dummy variables for different regime contexts as controls. More specifically, six regime contexts were created, identifying the welfare regimes of European countries following the literature (Esping-Andersen, 1990; Fenger, 2007; Kammer et al., 2012; Sapir, 2006). The classification framework for six welfare regimes for 36 countries in Europe is set out below (see Table A11). The countries remain in the same groups in all timeframes and regressions.

Socio-demographic characteristics of sectors in countries

We control for socio-demographic influences that may affect the outcome indicators: age, gender, and educational level. We expect that there exist differences between age groups in terms of skills due to cohort effects. For this reason, a control group of workers under the age of 30 was used. As workplaces are gendered in most cases and work changes have been found to affect female-dominated occupations differently from male-dominated occupations, a control for the proportion of men in a sector-country cell was also used (Bradley, 2015; Estevez-Abe, 2005). The third socio-economic influence relevant to this analysis about skills and tasks is the educational level of workers, where control was used for the proportion of highly educated workers (with tertiary education) in the sector-country cells. Details on the coding can be found in the annex (see Table A12).

3.3 Regression models

For this report, regressions are conducted in four steps to better understand the model building. In step 1, the two core inputs of the technological transformation, the Digital technology adoption and use indicator and the Learning capacity of the organisation indicator, are regressed on the dependent variable. In step 2, their interaction effect is added, followed in in step 3 by the welfare regime variables and in step 4 by the control variables.

Table 1 1 shows the independent and dependent variables of the regressions.

Table 1 Independent and dependent variables used for regressions

Independent variables	Dependent variables
Learning capacity indicator	ISCO [overall change between t0 and t1]
Digital technology adoption and use indicator	ISCO: ISCO categories 1 to 10 [change between t0 and t1]
Interaction term Digital technology adoption and use indicator/learning capacity indicator	Skill match
Welfare regimes (introduced as dummy variables)	Under-skilled
Share of employees with a high level of education	Over-skilled
Share of male employees (sex)	Increase of tasks and duties
Share of employees younger than 30 (age)	

Note: If not specified, the versions from t_1, t_0 and the change between t_1 and t_0 were used.

For accuracy, both Δt_{01}, the change of variables between t_0 (2010/11) and t_1 (2014/15) and their expression at those two points in time were used in our analysis. For the change variables, the values from t_0 were subtracted from the values from the first points in time t_1. Thus, generally – with one exception (see below) - there were three relevant timeframes:

1. t_1 2014/2015
   = independent/dependent variables of 2014/15 + time constant variables)
2. t_0 2010/2011
   = independent/dependent variables of 2010/11 + time constant variables
3. Δt_{01} Change between t_0 and t_1
   = independent and dependent variables as variables of change + time constant variables

An exception were the models on change of the overall occupational structure (see section 4.3), as more than one point in time is necessary to measure change. Here, only the change in the occupational structure between the two timeframes was used as the dependent variable for the model on the occupational structure.

4. Results and interpretation

In the next section, we first examine whether the number of tasks tends to increase, decrease or remain constant for workers depending on the level of inputs into the technological transformation and their evolution.

We then look at the effect of inputs into the technological transformation on skill (mis-)match as reported by employees in the sectors before we look at how the occupational structure is developing in relation to digital technologies and Learning capacity present and developing in the sectors. We do this in each case by first examining the relationship between the dependent and independent variables using the methods of descriptive bivariate statistics, before carrying out regression analyses in each case in a second step.

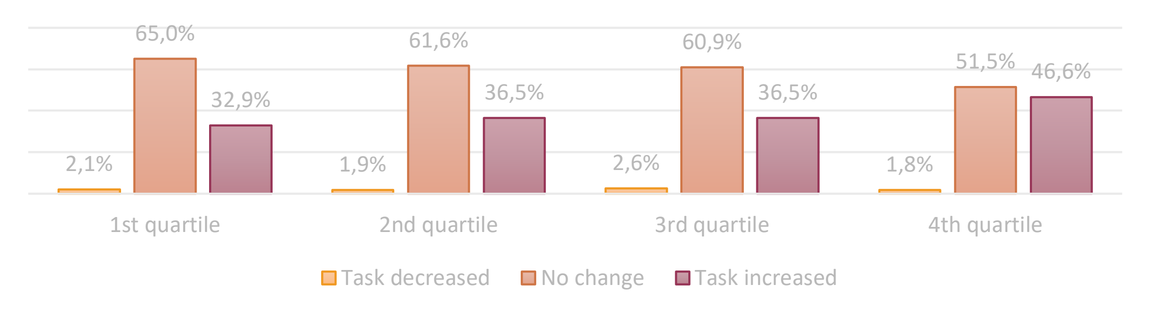
4.1 Change of tasks

As the question of *whether the number of tasks increased, decreased or stayed the same* over the last twelve months was only introduced in 2015 (t_1) in the EWCS, we cannot compare a change in answers. However, we can look at the influence of the status of the independent variables (t_1), such as the digital technology use, and we can have a look at the influence of change within these independent variables on the answers (t_1).

On average, for three-fifths (60%, standard deviation, σ 15%) of the employees in a sector-country cell the number of tasks remained unchanged within the last 12 months, whereas for almost two-fifths (38 per cent, σ 15 %), the number of tasks increased. The proportion of those whose tasks decreased was minimal (only 2 per cent, σ 4 %), with more than the half of all country-sector cells (130) having a proportion of 0 per cent of employees whose tasks decreased.

Looking at the proportions of the variable in the four quartiles of digital technology status (see Figure 2), it becomes apparent that the proportion of people who stated that their number of tasks neither increased or decreased, declines with higher technology status and the proportion of people with an increase of tasks rises in line with higher technology status. At the same time, the proportion of people with a decrease of tasks stays more or less the same. This connection between digital technology status and change of tasks is also supported by a correlation analysis (see Table A13).

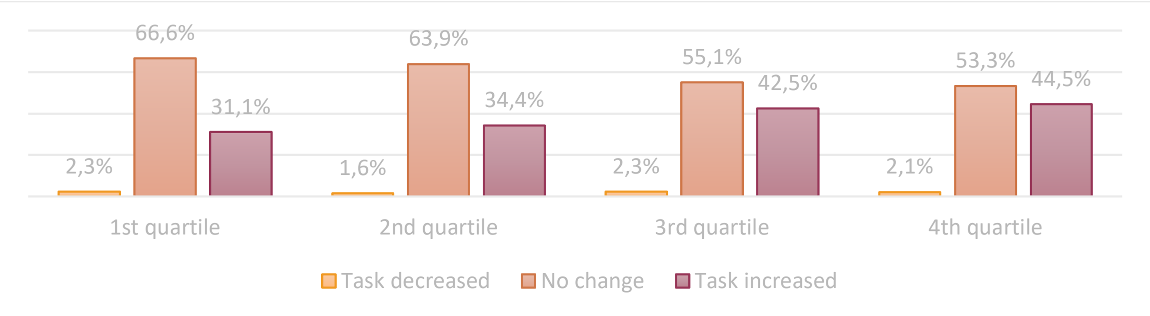
Figure 2 Proportion of task change within digital technology status (t_1) quartiles.



Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

The Learning capacity of the organisation seems to be similarly connected to increase and decrease of tasks (see Figure 3): In sectors where organisations have high Learning capacity, tasks are more likely increasing and less likely staying constant. This link is also supported by a correlation analysis (see Table A13). Besides these connection points, there are also corresponding correlation between the change of digital technology and Learning capacity status (Δt_{01}) with the task change variables (ibid.).

Figure 3 Proportion of task change within Learning capacity status (t_1) quartiles.



Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

Table 2 Regression on the proportion of employees that detected an increase of tasks in t_1.

		Independent variables: t_1			Independent variables: Δt_{01}		
		B	Sig.	SE B	B	Sig.	SE B
Step 1	Constant	0.02		0.06	0.35	***	0.02
	Digital technology indicator t_1 / Δt_{01}	0.22	**	0.07	0.22	*	0.11
	Learning Capacity indicator t_1 / Δt_{01}	0.44	***	0.11	0.11		0.11
	Adj. R^2		0.18			0.09	
Step 2	Constant	-0.19		0.26	0.35	***	0.02
	Digital technology indicator t_1 / Δt_{01}	0.60		0.47	0.19	.	0.11
	Learning Capacity indicator t_1 / Δt_{01}	0.80	.	0.45	0.22		0.22
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-0.66		0.80	-0.70		1.17
	Adj. R^2		0.18			0.08	
Step 3	Constant	-0.36		0.27	0.40	***	0.03
	Digital technology indicator t_1 / Δt_{01}	0.83	.	0.48	0.18		0.11
	Learning Capacity indicator t_1 / Δt_{01}	1.01	*	0.46	0.19		0.22
	Welfare Regimes: Southern	0.02		0.03	-0.06	.	0.03
	Welfare Regimes: Liberal	0.00		0.04	-0.01		0.04
	Welfare Regimes: Conservative	0.00		0.03	-0.05		0.03
	Welfare Regimes: Former USSR (Baltic)	-0.02		0.04	-0.10	*	0.04
	Welfare Regimes: Post-communist	0.07	.	0.03	-0.04		0.03
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-0.95		0.82	-0.84		1.18
	Adj. R^2		0.19			0.09	
Step 4	Constant	-0.22		0.28	0.39	***	0.03
	Digital technology indicator t_1 / Δt_{01}	0.57		0.49	0.20	.	0.11
	Learning Capacity indicator t_1 / Δt_{01}	0.74		0.47	0.19		0.22
	Welfare Regimes: Southern	0.03		0.04	-0.07	*	0.04
	Welfare Regimes: Liberal	0.01		0.04	-0.01		0.04
	Welfare Regimes: Conservative	0.01		0.03	-0.05		0.03
	Welfare Regimes: Former USSR (Baltic)	-0.02		0.04	-0.10	*	0.04
	Welfare Regimes: Post-communist	0.07	*	0.03	-0.04		0.03
	Share of high level of education t_1 / Δt_{01}	0.00		0.06	0.12		0.18
	Share of male employees t_1 / Δt_{01}	-0.07		0.07	-0.33		0.25
	Share of employees younger than 30 t_1 / Δt_{01}	0.22	*	0.11	0.35		0.21
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-0.53		0.83	0.22		1.21
	Adj. R^2		0.20			0.14	
	Number of observations		256			256	

*NOTE: . - $P \leq 0.1$ / * - $P \leq 0.05$ / ** - $P \leq 0.01$ / *** - $P \leq 0.001$ — Welfare regime variables are time-constant — Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

Looking at the regression results with independent variables from t_1 (see Table 2), the observed connections can also be found, but only in a part of the regression steps. The link between technological status and the increase in tasks can only be found in the first and the third step. The learning capacity indicator is more stable and has a significant positive effect in all but the last regression step. A higher learning capacity of the organisation seems to go hand in hand with a higher increase in the number of tasks. The post-Communist welfare regime has a slight positive significant effect in the third and fourth regression steps. The proportion of young employees also has a slightly positive effect on the increase in tasks. The interaction term is not significant in any of the steps in the model.

In the model that looks at the effects of the change in technology (Δt_{01}) use on task numbers given in t_1 (see also Table 2), the change in technology shows a positive effect on the increase of tasks in all but the third regression step. The change in Learning capacity has no significant effect. In the third and fourth regression steps, the Baltic / former USSR and southern welfare states significantly negatively affect the increase of tasks during the last 12 months.

Overall, the results support the idea that **employees in country-sector cells with high technology status and a high level of technological change tend to be more likely to perceive an increase** in **their tasks**. Also, the **learning capacity of the organisation seems to** affect the likelihood of this perception positively. However, these effects were only stable to a limited extent - in the last regression step, only one of the four mainly relevant coefficients was significant.

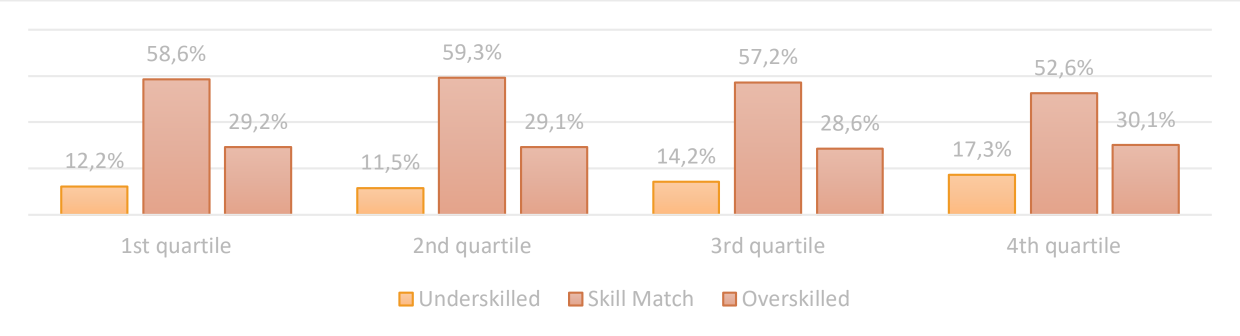
4.2 Skill match/mismatch

An increase of tasks, i. e. a change of tasks, may also have potential effects on the skill (mis-)match – therefore, we will now explore whether technological advances lead to mismatches between tasks and employees' skills. The question will be examined in two ways. Firstly, it will be determined whether the technology status of companies is associated with a higher or lower skill match, and secondly, it will be determined whether an increase in technology usage between t_0 and t_1 is associated with an increase or decrease in skill match during the same time period. We look at the proportion of employees reporting a skill match, as well as the proportion of over-skilled and under-skilled employees. On average, results from the 2015 survey data (t_1) revealed that in the country-sector cells, the rate of workers categorising themselves as "under-skilled" was about 14%, with 57% categorized themselves as having "skill match" and a further 29% categorised themselves as "over-skilled".

Comparing the proportions of under-skilled, skill-matched, and over-skilled workers by quartile of the technology status (t_1), it becomes apparent that the skill match seems lowest among sectors found in the highest quartile (4^{th}) of technology status (

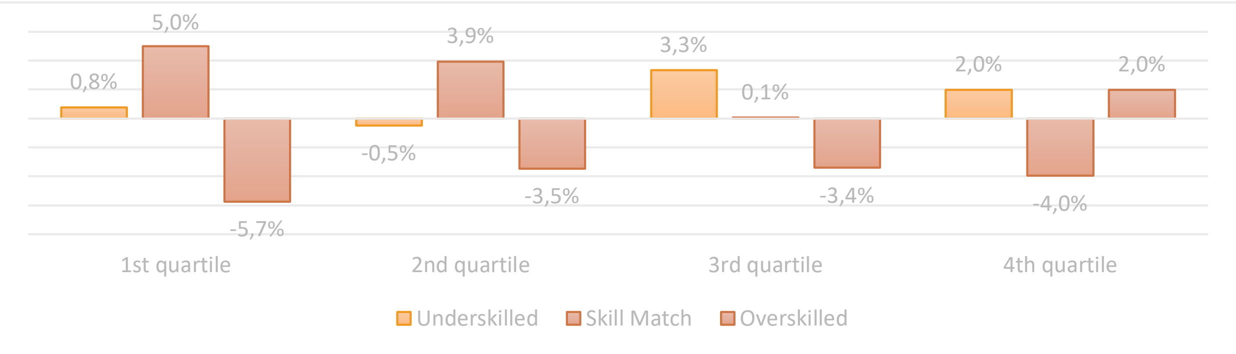
Figure 4). At the same time, the proportion of under-skilled people grows with higher technology use. This is also supported by the correlation analysis (see Table A14).

Figure 4 Proportions of under-skilled, skill match and over-skilled in four quartiles of the Digital technology adoption and use indicator (t_1)



Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

Figure 5 Change of proportions of under-skilled, skill match and over-skilled in quartiles of the change of the Digital technology adoption and use indicator (Δt_{01})

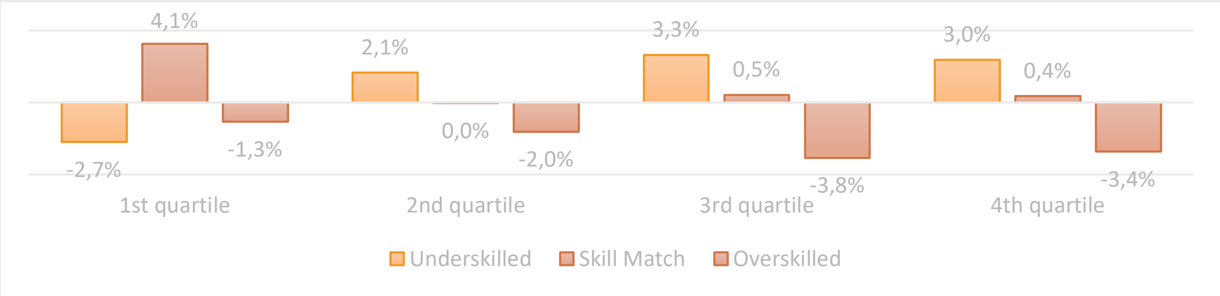


Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

However, slightly different results emerge when looking at the change of the skill match indicators (Δt_{01}), contextualised by the quartiles of the change of the technology indicator (Δt_{01}, see Figure 5). In country-sector skills that did not change much regarding their technology status from t_0 to t_1 (1st quarter), the proportion of employees with skill match grew by five percentage points, whereas the proportion of over-skilled people declined by 5.7 percentage points. In contrast to this, the skill match of employees in sectors with high uptake of technology declined by 4 per cent, whereas the proportion of over-skilled and under-skilled employees grew by 2 per cent each. Again, these results are confirmed with three significant correlations (see Table A14).

The proportions of under-skilled, skill match and over-skilled change differ in the quartiles of the change of the Learning capacity indicator (see Figure 6). A low change in the Learning capacity indicator is associated with an increase in the proportion of skill match (1st quartile). Nevertheless, with a higher change of the Learning capacity of the organisation (2nd to 4th quartile), the skill match stays more or less constant, while the proportions of under-skilled and over-skilled evolve differently. The proportion of over-skilled people decreases with a higher increase in Learning capacity, whereas the proportion of under-skilled people is increasing. This denotes a more intense use of skills. In the correlation analysis, the effects regarding the change of the proportion of under-skilled people and people with a match of skills and task could be confirmed (see Table A14).

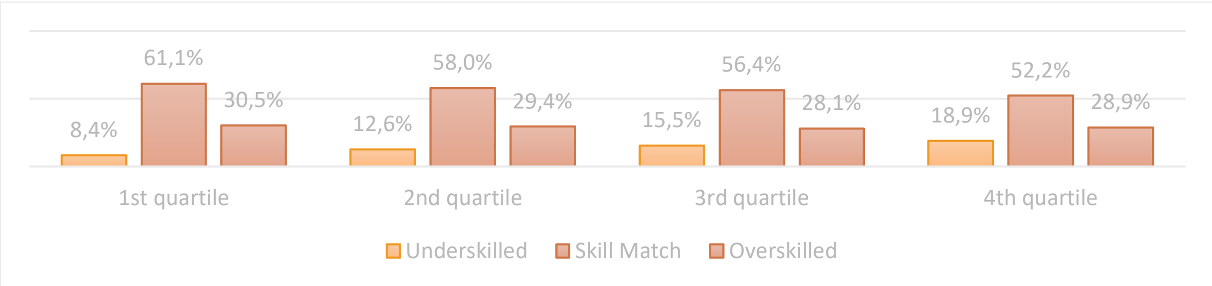
Figure 6 Change of proportions of under-skilled, skill match and over-skilled in quartiles of the change of the Learning capacity indicator (Δt_{01})



Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

Figure 7 show the proportions of skill (mis-)match in the four quartiles of Learning capacity of organisation at t_1. Here, the proportion of under-skilled people seems to be increasing with higher learning capacity, whereas the proportion of people with a skill match is declining. Both effects are supported through the correlation analysis (see Table A14).

Figure 7 Proportions of under-skilled, skill match and over-skilled in four quartiles of the Learning Capacity indicator (t_1)



Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

Regarding the t_1 regressions on the proportion of skill match (see Table 3), a higher Digital technology adoption and use indicator is associated with a lower share of employees with a skills match, but only in the first steps. This effect cannot be found when adding the interaction term and the other variables, such as the welfare regimes and the socio-demographic variables, into the linear model. The effect becomes positive but it is no longer significant.

Table 3 Regression on the proportion of employees with a skill match in t_1 and the change of the proportion of employees with a skill match (Δt_{01})

		t_1			Δt_{01}		
		B	Sig.	SE B	B	Sig.	SE B
Step 1	Constant	0.79	***	0.06	0.09	***	0.02
	Digital technology indicator t_1 / Δt_{01}	-0.12	.	0.07	-0.53	***	0.13
	Learning Capacity indicator t_1 / Δt_{01}	-0.28	**	0.10	-0.31	*	0.14
	Adj. R^2		0.06			0.07	
Step 2	Constant	0.50	*	0.25	0.09	***	0.03
	Digital technology indicator t_1 / Δt_{01}	0.42		0.46	-0.50	***	0.14
	Learning Capacity indicator t_1 / Δt_{01}	0.22		0.44	-0.45	.	0.27
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-0.92		0.78	0.91		1.48
	Adj. R^2		0.06			0.07	
Step 3	Constant	0.52	*	0.26	0.04		0.04
	Digital technology indicator t_1 / Δt_{01}	0.59		0.47	-0.51	***	0.14
	Learning Capacity indicator t_1 / Δt_{01}	0.37		0.45	-0.35		0.27
	Welfare Regimes: Southern	-0.07	*	0.03	0.06		0.04
	Welfare Regimes: Liberal	-0.07	.	0.04	0.11	.	0.05
	Welfare Regimes: Conservative	-0.10	**	0.03	-0.01		0.04
	Welfare Regimes: Former USSR (Baltic)	-0.08	*	0.04	0.06		0.05
	Welfare Regimes: Post-communist	-0.09	**	0.03	0.08	*	0.04
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-1.31	.	0.79	0.42		1.50
	Adj. R^2		0.08			0.09	
Step 4	Constant	0.45		0.28	0.07		0.04
	Digital technology indicator t_1 / Δt_{01}	0.62		0.48	-0.57	***	0.14
	Learning Capacity indicator t_1 / Δt_{01}	0.49		0.46	-0.33		0.27
	Welfare Regimes: Southern	-0.05		0.04	0.08	.	0.04
	Welfare Regimes: Liberal	-0.05		0.04	0.11	*	0.05
	Welfare Regimes: Conservative	-0.08	*	0.03	-0.01		0.04
	Welfare Regimes: Former USSR (Baltic)	-0.05		0.04	0.05		0.05
	Welfare Regimes: Post-communist	-0.07	*	0.03	0.08	.	0.04
	Share of high level of education t_1 / Δt_{01}	-0.11	.	0.06	-0.21		0.22
	Share of male employees t_1 / Δt_{01}	0.02		0.06	0.70	*	0.31
	Share of employees younger than 30 t_1 / Δt_{01}	-0.05		0.11	0.35		0.26
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-1.28		0.81	0.52		1.51
	Adj. R^2		0.09			0.11	
	Number of observations		256			255[2]	

*NOTE: . - $P \leq 0.1$ / * - $P \leq 0.05$ / ** - $P \leq 0.01$ / *** / $P \leq 0.001$ — Welfare regime variables are time-constant — Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

[2] 1 case was deleted due to a high Cooks Distance value

The Learning capacity indicator reduces the proportion of employees with a skill match in the first regression step. However, this effect is also no longer significant when the other variables are added to the model. The interaction term is negative and significant in regression step 3, but not significant in the other regression steps. This is a small indication that sectors with high Digital technology and high Learning capacity tend to have a lower level of skill match – contrary to our predictions (see H3.4). Compared to the social-democratic welfare regime, the other five welfare regimes tend to perform worse when it comes to skill match; all are significantly negatively associated with the proportion of skill match in a sector in regression step 3. This effect can still be found in the conservative welfare regimes and the post-Communist welfare regimes in step 4. Regarding the socio-demographic variables, there is only a significant negative effect of higher education on skill match in step 4.

In the Δt_{01} regressions (see Table 3), it is interesting to see that positive development of the Digital technology indicator is associated with a decline in the share of employees stating that their skills match their tasks. This effect remains robust even when integrating other variables into the model. This result indicates that an increasing use of digital technologies induces changes in the work set-up for employees. The share of employees who notice neither a lack of skills nor unused skills in their daily work decline, regardless of the individual starting points of the sectors. Also, an increase in the learning capacity of the organisation is associated with a negative development of the proportion of employees with skill match. The interaction term stays insignificant in all steps of the regression.

These results only confirm to a very limited extent that digitalisation and learning capacity of the organisation fosters a lower skill (mis-)match in sectors. Therefore, we also look at the regression results on the proportions and changes of under-skilled employees (see Table 4). Again, it becomes apparent that the t_1 Digital technology indicator has a significant positive effect on the proportion of people being under-skilled (t_1), but only in the first regression step, making the result not robust. By contrast, the effect of the Learning capacity indicator remains significant and positive throughout the regression steps, meaning that a higher learning capacity of the organisation is associated with a higher proportion of people being under-skilled, even when controlling for technology status. Taking the interaction term into the regressions improves the models only marginally (improvement Adj. R^2 for Step 3 = .003), as the term is not significant in any of the models for the later point in time (t_1). Regarding public policy, the comparison showed that conservative welfare states, Baltic (former USSR) states, and Post-Communist welfare states had a positive influence on the proportion of people being under-skilled. A higher share of highly educated employees also has a (small) positive effect on the share of under-skilled people.

The regression in the change of the proportion of under-skilled employees (see Table 4) provides similar results. First, the change of the technology indicator stays insignificant in all regression steps, whereas at the same time, the change in the Learning capacity indicator has a positive influence on under-skilling, meaning that the proportion of people who report being under-skilled increases with higher average learning capacity of the organisation. The interaction term, at the same time, is negative and insignificant in all regression steps.

Table 4 Regression on the proportion of employees being under-skilled in (t_1) and the change of the proportion of employees being under-skilled (Δt_{01})

		t_1			Δt_{01}		
		B	Sig.	SE B	B	Sig.	SE B
Step 1	Constant	-0.10	*	0.04	0.02		0.01
	Digital technology indicator t_1 / Δt_{01}	0.10	.	0.05	0.01		0.08
	Learning Capacity indicator t_1 / Δt_{01}	0.33	***	0.08	0.23	**	0.09
	Adj. R^2		0.11			0.02	
Step 2	Constant	-0.34	.	0.19	0.02		0.02
	Digital technology indicator t_1 / Δt_{01}	0.55		0.34	-0.01		0.08
	Learning Capacity indicator t_1 / Δt_{01}	0.75	*	0.33	0.44	.	0.24
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-0.77		0.58	-1.23		1.32
	Adj. R^2		0.11			0.02	
Step 3	Constant	-0.39	*	0.19	0.04		0.02
	Digital technology indicator t_1 / Δt_{01}	0.42		0.34	-0.03		0.08
	Learning Capacity indicator t_1 / Δt_{01}	0.69	*	0.32	0.42	.	0.25
	Welfare Regimes: Southern	0.05	*	0.02	-0.01		0.02
	Welfare Regimes: Liberal	-0.01		0.03	-0.01		0.03
	Welfare Regimes: Conservative	0.09	***	0.02	-0.01		0.02
	Welfare Regimes: Former USSR (Baltic)	0.14	***	0.03	0.02		0.03
	Welfare Regimes: Post-communist	0.06	**	0.02	-0.05	*	0.02
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-0.46		0.57	-1.01		1.34
	Adj. R^2		0.21			0.04	
Step 4	Constant	-0.35	.	0.20	0.03		0.03
	Digital technology indicator t_1 / Δt_{01}	0.45		0.34	-0.02		0.09
	Learning Capacity indicator t_1 / Δt_{01}	0.65	*	0.33	0.45	.	0.25
	Welfare Regimes: Southern	0.03		0.02	-0.01		0.03
	Welfare Regimes: Liberal	-0.02		0.03	-0.01		0.03
	Welfare Regimes: Conservative	0.07	**	0.02	-0.01		0.03
	Welfare Regimes: Former USSR (Baltic)	0.12	***	0.03	0.02		0.03
	Welfare Regimes: Post-communist	0.05	.	0.02	-0.04	.	0.02
	Share of high level of education t_1 / Δt_{01}	0.08	*	0.04	0.09		0.13
	Share of male employees t_1 / Δt_{01}	0.00		0.05	-0.20		0.19
	Share of employees younger than 30 t_1 / Δt_{01}	-0.03		0.08	-0.03		0.17
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	-0.58		0.58	-1.23		1.37
	Adj. R^2		0.22			0.03	
	Number of observations		256			254[3]	

NOTE: . - P ≤ 0.1 / * - P ≤ 0.05 / ** - P ≤ 0.01 / *** - P ≤ 0.001 — Welfare regime variables are time-constant *Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

[3] 2 cases were deleted due to high Cooks Distance values

Table 5 Regression on the proportion of employees being over-skilled in t_1 and the change of the proportion of employees being over-skilled (Δt_{01})

		t_1			Δt_{01}		
		B	Sig.	SE B	B	Sig.	SE B
Step 1	Constant	0.30	***	0.05	-0.10	***	0.02
	Digital technology indicator t_1 / Δt_{01}	0.02		0.07	0.46	***	0.13
	Learning Capacity indicator t_1 / Δt_{01}	-0.04		0.10	-0.09		0.14
	Adj. R^2		0.01			0.04	
Step 2	Constant	0.84	***	0.24	-0.09	***	0.02
	Digital technology indicator t_1 / Δt_{01}	-0.97	*	0.44	0.43	**	0.13
	Learning Capacity indicator t_1 / Δt_{01}	-0.97	*	0.42	0.22		0.38
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	1.69	*	0.74	-1.77		2.04
	Adj. R^2		0.01			0.04	
Step 3	Constant	0.87	***	0.25	-0.06		0.04
	Digital technology indicator t_1 / Δt_{01}	-1.00	*	0.44	0.45	***	0.13
	Learning Capacity indicator t_1 / Δt_{01}	-1.05	*	0.43	0.12		0.39
	Welfare Regimes: Southern	0.01		0.03	-0.05		0.04
	Welfare Regimes: Liberal	0.08	*	0.04	-0.09	.	0.05
	Welfare Regimes: Conservative	0.01		0.03	0.00		0.04
	Welfare Regimes: Former USSR (Baltic)	-0.06	.	0.04	-0.09	.	0.05
	Welfare Regimes: Post-communist	0.03		0.03	-0.03		0.04
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	1.78	*	0.75	-1.40		2.07
	Adj. R^2		0.04			0.05	
Step 4	Constant	0.91	***	0.26	-0.06		0.04
	Digital technology indicator t_1 / Δt_{01}	-1.07	*	0.46	0.48	***	0.14
	Learning Capacity indicator t_1 / Δt_{01}	-1.14	**	0.44	0.09		0.39
	Welfare Regimes: Southern	0.01		0.03	-0.07		0.04
	Welfare Regimes: Liberal	0.08	.	0.04	-0.10	.	0.05
	Welfare Regimes: Conservative	0.01		0.03	0.00		0.04
	Welfare Regimes: Former USSR (Baltic)	-0.07	.	0.04	-0.09	.	0.05
	Welfare Regimes: Post-communist	0.03		0.03	-0.04		0.04
	Share of high level of education t_1 / Δt_{01}	0.03		0.05	-0.11		0.21
	Share of male employees t_1 / Δt_{01}	-0.01		0.06	-0.46		0.30
	Share of employees younger than 30 t_1 / Δt_{01}	0.08		0.10	-0.23		0.25
	Digital technology indicator x Learning Capacity indicator t_1 / Δt_{01}	1.86	*	0.78	-1.31		2.11
	Adj. R^2		0.04			0.05	
	Number of observations		256			255[4]	

NOTE: . - P ≤ 0.1 / * - P ≤ 0.05 / ** - P ≤ 0.01 / *** / P ≤ 0.001 — Welfare regime variables are time-constant — *Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

[4] 1 case was deleted due to high Cooks Distance value

Table 5 displays the regression models on the share of over-skilled employees in country-sector cells. The Digital technology indicator is not significant at first, only becoming significant in step 2, when the interaction term is added to the model, and it then has a negative influence on the share of over-skilled people on its own. The interaction term is significant with a bigger effect than the two main effects on their own, indicating that sectors that are both advanced in the utilisation of digital technologies and in their learning capacity tend to produce more over-skilled people.

In all four steps of the regressions with the change of the share of employees who are over-skilled (see Table 5), the change of Digital technology indicator has a significant positive effect on the change of over-skilled employees. This allows for a different interpretation of the results; assuming that technological change leads to changed tasks, digital technological change can also contribute to employees not being able to use their skills sufficiently at work.

If we run the same regressions for the earlier time point in the data set (t_0, data from 2010/2011), the effects mostly go in a similar direction for both skill match and under-skilled (see Table A16, annex). However, it is notable that in contrast to the t_1 regression,

- the digital technology indicator has no significant effect on skill match in all five regression steps,
- the Learning capacity indicator has a less strong effect on skill match.

At the same time, the negative influence of the types of welfare states (except the negative effect of the conservative welfare state regimes) on skill match was stronger (and significant) in t_0 than in t_1, possibly explained by a decline in the importance of welfare policies or convergence between the policies between t_0 and t_1. The results of the regressions for the dependent variable "under-skilled" for the earlier time point in the data set (t_0) were similar to the t_1 regressions, however, the results regarding the technology and the Learning capacity indicator were not as robust as the data from t_1 showed (similar to the time differences for the skill match regressions).

4.3 Structure of occupations

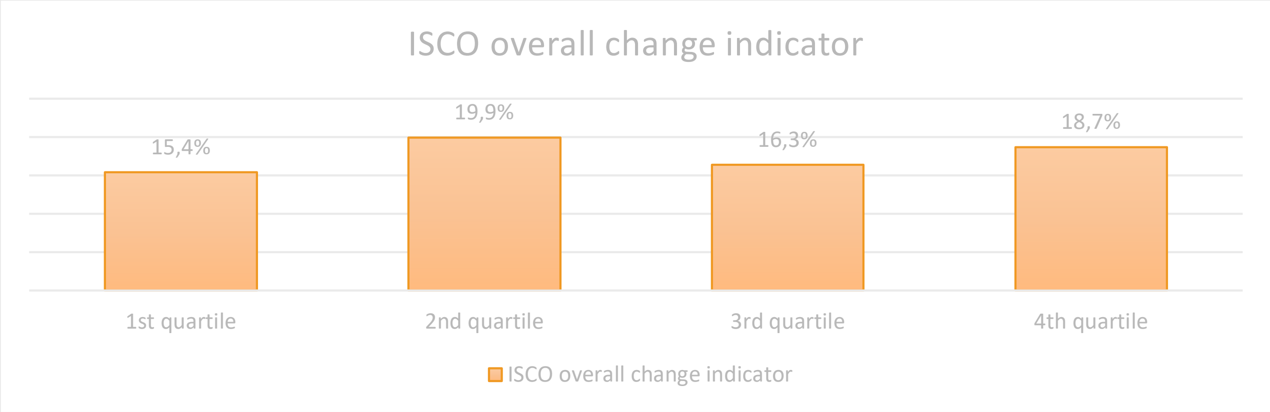
With the dataset of the BEYOND 4.0 project, we can look at changes in shares of the ISCO 08 groups. We look at both changes in the shares of single ISCO 1-digit groups and the overall change of ISCO groups to capture the change in the occupational structure of the sectors in countries.

Overall change

Looking at the size of the ISCO overall change indicator in the four quartiles of digital technology status in t_0[5] , a clear trend is not identifiable (see Figure 8), and neither is there a clear correlation (see Table A15, annex). In addition, there is no significant correlation between the change of the digital technology indicator and the ISCO overall change indicator.

[5] t_0 is taken here because it seems not logical that the technology status of t_1 may have an influence on the change of the occupational structure between t_0 and t_1.

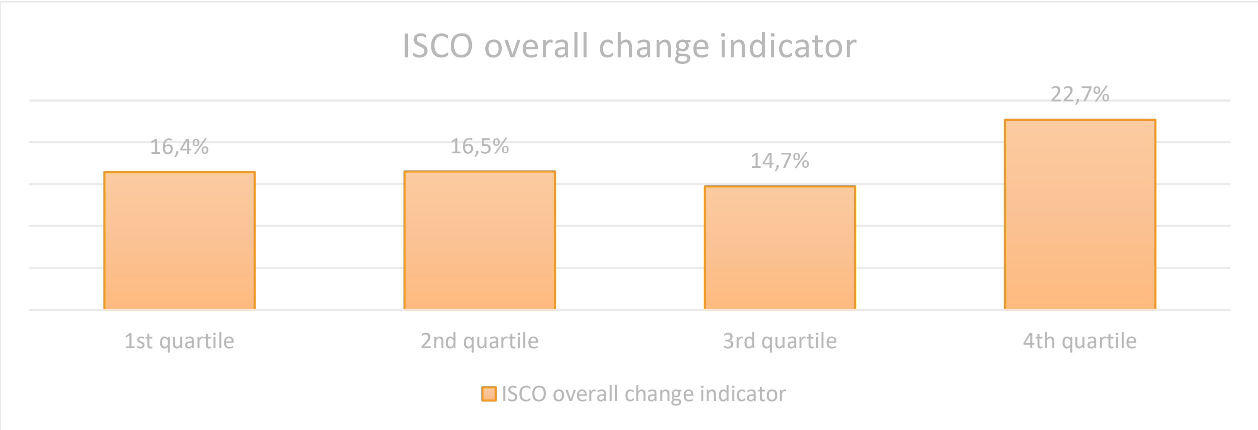
Figure 8 ISCO overall change indicator by digital technology status (t_0).



Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

The ISCO overall change indicator is clearly higher in the fourth quartile of the Learning capacity indicator (see Figure 9) resulting in a significant positive correlation (see Table A15).

Figure 9 ISCO overall change indicator by Learning capacity Indicator (t_0)



Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

The model calculated with the earlier status of the independent variables (t_0) (see Table 6) shows a significant positive effect of the digital technology indicator (t_0) on the change of the occupational structure in the sectors in countries in steps 2, 3 and 4. The same holds true for the Learning capacity indicator for steps 3 and 4. The interaction term has a high negative estimate thus showing that the change of occupational structure is not as strong in those sectors with both a high Learning capacity and a high digital technological status in t_0.

The results of the model on change show no significant effect of the change of the Digital technology and Learning capacity indicators on the change of the occupational structure, as measured by the change in total proportions of ISCO categories in sectors (see Table 6). Other influences on change of occupational structure are significant: Liberal welfare regimes (negatively correlated), the Conservative and the Baltic (former USSR) welfare states (positively correlated) as well as the age structure, where an increase in the proportion of younger employees in a sector has a positive effect on the change of occupations within the same sector.

Table 6 Regression on the change of the occupational structure (in absolute values, $|\Delta t_{01}|$) and influences from the earlier point in time (t_0).

		Independent variables: t_0			Independent variables: Δt_{01}		
		B	Sig.	SE B	B	Sig.	SE B
Step 1	Constant	0.07	.	0.04	0.17	***	0.01
	Digital technology indicator t_0 / Δt_{01}	-0.03		0.06	0.04		0.07
	Learning Capacity indicator t_0 / Δt_{01}	0.22	**	0.07	-0.11		0.07
	Adj. R^2		0.03			0.01	
Step 2	Constant	-0.25	.	0.14	0.17	***	0.01
	Digital technology indicator t_0 / Δt_{01}	0.73	*	0.33	0.04		0.07
	Learning Capacity indicator t_0 / Δt_{01}	0.79	**	0.25	-0.11		0.20
	Digital technology indicator x Learning Capacity indicator t_0 / Δt_{01}	-1.34	*	0.57	-0.04		1.10
	Adj. R^2		0.05			0.00	
Step 3	Constant	-0.31	*	0.14	0.14	***	0.02
	Digital technology indicator t_0 / Δt_{01}	0.74	*	0.33	0.05		0.07
	Learning Capacity indicator t_0 / Δt_{01}	0.81	**	0.25	-0.14		0.20
	Welfare Regimes: Southern	0.06	**	0.02	0.05	*	0.02
	Welfare Regimes: Liberal	-0.05	.	0.03	-0.03		0.03
	Welfare Regimes: Conservative	0.04	*	0.02	0.04	*	0.02
	Welfare Regimes: Former USSR (Baltic)	0.06	*	0.03	0.07	**	0.02
	Welfare Regimes: Post-communist	0.03		0.02	0.01		0.02
	Digital technology indicator x Learning Capacity indicator t_0 / Δt_{01}	-1.29	*	0.56	0.41		1.08
	Adj. R^2		.11			.06	
Step 4	Constant	-0.20		0.14	0.13	***	0.02
	Digital technology indicator t_0 / Δt_{01}	0.72	*	0.32	0.07		0.07
	Learning Capacity indicator t_0 / Δt_{01}	0.79	**	0.24	-0.10		0.20
	Welfare Regimes: Southern	0.04	.	0.02	0.02		0.02
	Welfare Regimes: Liberal	-0.07	*	0.03	-0.05	.	0.03
	Welfare Regimes: Conservative	0.03		0.02	0.03	.	0.02
	Welfare Regimes: Former USSR (Baltic)	0.03		0.03	0.06	*	0.02
	Welfare Regimes: Post-communist	0.00		0.02	0.00		0.02
	Share of high level of education t_0 / Δt_{01}	0.12	**	0.04	0.10		0.11
	Share of male employees t_0 / Δt_{01}	-0.09	*	0.04	-0.09		0.15
	Share of employees younger than 30 t_0 / Δt_{01}	-0.04		0.07	-0.33	*	0.13
	Digital technology indicator x Learning Capacity indicator t_0 / Δt_{01}	-1.45	**	0.55	0.21		1.08
	Adj. R^2		0.17			0.08	
	Number of observations		253[6]			253[6]	

NOTE: . - P ≤ 0.1 / * - P ≤ 0.05 / ** - P ≤ 0.01 / *** / P ≤ 0.001 — n = 253 (in both regressions, 3 case were deleted due to high Cooks Distance value) — Welfare regime variables are time-constant — *Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

[6] 3 cases were deleted due to high Cook Distance values.

Change of major ISCO groups

On the 1-digit level of the ISCO 08 occupational groups, the ISCO classification differentiates the ISCO categories by field of knowledge and discipline but also the educational level that is usually required to work in that occupation. The digitalisation of work has different effects on different occupations. Looking at the changes of proportion within these categories, Professionals (ISCO group 2) and Clerical support workers (ISCO group 4) stand out, as their change in highly technicised country-sector cells is both particularly high.

Table 7 Proportion change of ISCO groups by digital technology status of t_0 (in quartiles)

Technology status	1st quartile	2nd quartile	3rd quartile	4th quartile
1. Managers	0.16 %	0.24 %	0.12 %	- 0.19 %
2. Professionals	0.64 %	0.30 %	1.10 %	3.45 %
3. Technicians and associated professionals	0.26 %	- 0.38 %	- 0.60 %	- 0.14 %
4. Clerical support workers	- 0.54 %	- 0.51 %	- 0.57 %	- 2.33 %
5. Service and sales workers	- 0.44 %	- 0.01 %	- 0.67 %	- 0.10 %
6. Skilled agricultural, forestry and fishery workers	0.02 %	- 0.07 %	- 0.02 %	- 0.05 %
7. Craft related trades workers	- 0.14 %	- 0.01 %	- 0.43 %	-0.71 %
8. Plant and machine operators, and assemblers	- 0.00 %	0.42 %	0.17 %	- 0.29 %
9. Elementary occupations	0.03 %	0.04 %	-0.45 %	0.25 %
0. Armed forces occupations	0.01 %	- 0.01 %	0.02 %	0.12 %

Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.

In fact, the change of these two ISCO occupational groups both correlate significantly with the t_0 digital technology status (see Table A15).

However, when looking at changes in the proportions in the major occupational groups, the change of the digital technology indicator over time has no significant effect on the change of the share of major occupational categories in our sample. In these models, it is rather the change of the Learning capacity indicator between t_0 and t_1 that is correlated with the change of Technicians and associate professionals (ISCO group 3) and Clerical support workers (ISCO group 4). The effects themselves, however, are opposing, with the change of the Learning capacity indicator having a positive effect on Clerical support workers and a negative effect on Technicians and associate professionals.

Noteworthy here, the interaction term of the change of the Learning capacity indicator and the change of the digital technology indicator is also significant in these models. For Clerical support workers, it shows a moderating effect (-1.60), thus dampening the effect of the Learning capacity when digital technology use rises. On the other way around, the interaction term has a significant positive effect with regard to Technicians and associate professionals, while the digital technology indicator is not significant, making it difficult to interpret a clear interaction.

The effects found by the correlation analysis between the increases and decreases in each ISCO occupational category and the 2010 technology status no longer show up in the full models.

Table 8 Regression on the change of two occupational groups with change variables as independent variables.

	Change of Technicians and associated professionals			Change of Clerical support workers		
	B	Sig.	SE B	B	Sig.	SE B
Constant	0.01	.	0.01	-0.01		0.01
Digital technology indicator Δt_{01}	-0.04		0.03	0.01		0.03
Learning Capacity indicator Δt_{01}	-0.12	*	0.06	0.27	***	0.05
Welfare Regimes: Southern	0.00		0.01	0.00		0.01
Welfare Regimes: Liberal	0.00		0.01	0.00		0.01
Welfare Regimes: Conservative	-0.02	.	0.01	0.00		0.01
Welfare Regimes: Former USSR (Baltic)	-0.01		0.01	0.01		0.01
Welfare Regimes: Post-communist	-0.02	*	0.01	0.01		0.01
Share of high level of education Δt_{01}	-0.02		0.05	-0.10	*	0.04
Share of male employeesΔt_{01}	0.05		0.06	-0.13	*	0.06
Share of employees younger than 30 Δt_{01}	0.02		0.05	-0.06		0.05
Digital technology indicator x Learning Capacity indicator Δt_{01}	0.91	**	0.31	-1.60	***	0.29
Adj. R^2	0.06			0.16		
Number of observations	256			256		

*NOTE: . - P ≤ 0.1 / * - P ≤ 0.05 / ** - P ≤ 0.01 / *** / P ≤ 0.001 — Welfare regime variables are time-constant — Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

5. Conclusion

Based on the above analysis, we reached a number of conclusions with regard to our hypotheses.

5.1 Change of tasks

Our analysis has shown a link between digital technology and the increase in tasks. For the second point in time (t_1) the analysis showed that the proportion of employees stating that their tasks increased is correlated with the size of the digital technology adoption and use indicator. Also, a change in digital technology status (Δt_{01}) is correlated with a change in the proportion of employees reporting an increase in the number of their tasks. These estimated relationships were both significant in the first step of the regression, but they become weaker as more variables are added to the model, the second one showing more robustness than the first one.

The results give reason to assume that H1.1 ("*Employees working in environments that are affected by technological change are more likely to experience an increase in their tasks*") does hold true. However, the other influences are also at play. In the regression with data from t_1, the Learning capacity indicator shows a more robust correlation with increasing tasks and duties than the digital technology indicator. These findings suggest that the effect of technological change has a clear impact on the number of tasks of employees but that the organisational characteristics play a stronger role. This effect is most likely due to the nature of the Learning capacity indicator, which measures the capacity of an organisation to make innovation possible. Learning capacity, as measured by the indicator, poses high requirements on employees in terms of tasks and skills. That is, complex tasks and problem-solving, bringing their own ideas into work, structuring, negotiating and evaluating their own tasks, autonomous teamwork and participatory involvement in the organisation of work is measured by the Learning capacity indicator. All of these add task and skill requirements on top of domain- or job-specific tasks and skill requirements. A similar observation can be found in research-based modern sociotechnical systems thinking (Dhondt et al., 2021). The researchers found that employees who experience a shift towards more "generic skills to fulfil preparation, supportive and regulating tasks" also experienced more skill use (showing that the overall tasks also increased), and vice versa[7]. These tasks are comparable to those measured by the Learning capacity indicator, although the latter encompasses a higher number of items.

5.2 Skill (mis-)match

On average, the higher the digital technology indicator in a sector in t_1, the lower the skill match when regressing technology and learning capacity on skill match. When we added more control variables to the regression, this relation did cease to be significant.

However, the negative correlation between change in the digital technology indicator and change of skill match proved to be more robust. In sectors where digital technology use increases, the

[7] Their approach divides tasks into four categories. One of them builds the core of tasks of jobs, the "executive tasks" but then the other three categories are more generic and can be used to distinguish organisations, or more specifically work environments.

share of workers feeling that their skills match their job decreases. Thus, all in all, the expected relationship between skill (mis-)match and technology, as presented in *H2.1* ("*Employees working in environments affected by high technology use or an increase in technology use are more likely to experience a mismatch between their own skills and the skills required to do their jobs."*) can be partly confirmed, at least with regard to the short-term dimension of change of skill match.

Looking deeper into this effect, two effects of digital technology use seem possible from a theoretical point of view. Either technology replaces some tasks so that employees' skills become economically obsolete (that is, they become over-skilled) or the use of technology leads to new skill requirements for employees so that they need further training to do their (new) tasks (that is, they become under-skilled).

The correlation and regression calculations shows that a distinction should be made between the effects of change and the effects of high status. One could argue that the former represent short-term effects whereas the latter describes long-term effects of the technological transformation. The results indicate, that an increase in technology status seem to go hand in hand with an increasing proportion of over-skilled employees. Exactly the opposite is the case with a high technology status, which has a negative influence on the proportion of over-skilled employees. Taken together, the more detailed look at skill mismatches reveals differences between the sectors that have a high technology status and those that have improved their status. With the help of further data, these differences could be examined more closely.

A higher learning capacity is linked with a lower likelihood of a match of skills and tasks –this effect can be found in the first step of the corresponding regression. Even more robust are the positive effects of the Learning capacity indicator on the proportion of under-skilled employees and negative effects on the proportion of over-skilled effect denoting the higher use of skills in learning organisations. Similar effects were also found in the change regressions between an increase in the learning capacity of the organisation and the increase of under skilled workers while the estimated relationship with the evolution of over-skilled workers remained non-significant.

Comparing digital technology and learning capacity results, an obvious common feature is that both have a negative impact on the proportion of over-skilled employees (status t_1). But interestingly, those sectors with both high digital technology use and high learning capacity also have a higher proportion of over-skilled employees (as the interaction term shows). It is possible that the employees who work in these highly innovative sectors are well qualified and cannot use some of their skills.

One way to understand these results is to view today's outcomes as tomorrow's inputs. This is especially true for the skills utilisation of employees by companies that want to achieve continuous improvement of productivity through innovation. A potential skill mismatch caused by technology uptake can potentially dampen the future innovative activities of companies, thus threatening a successful improvement in productivity in the long run. Therefore, skill mismatches should be kept in mind when investing in innovative capacity.

5.3 Structure of Occupations

The change of proportions of the different ISCO occupational categories in sectors in countries between t_0 and t_1 is positively influenced by the level of digital technology use in t_0. The higher the use of the measured technologies was in t_0, the greater the change in occupation, so *H3.1* ("*H3.1 Working environments that are affected by technological change are more likely to result in a change in the occupational structure.")* can be confirmed. Taking a close look at the proportion of single ISCO occupational categories, some of them correlate with the technology indicator, but there were no significant effects in the last steps of the regressions.

The effect of learning capacity at t_0 is even stronger and also influences the change of the occupational structure positively. Moreover, learning capacity has a guarding effect with less change in the occupational structure if both technology use and learning capacity are high in a sector (based on t_0 information). This finding then supports the idea of work design theory that emphasises the role of work organisation and organisational structure in the way technology impacts human resources. Also, the Socio-technological approaches perspective on how organisational, human and technological factors are interdependent receives some support from this analysis.

5.4 Learning Capacity of the organisation

The Learning capacity of the organisation indicator measures frequency and opportunity of work situations such as solving unforeseen problems, performing complex tasks, on-the-job training, assessing the quality of own work, teams who decide on their task division and timetables and further participation of employees in decisions about the organisation of their work. It stands to reason, that these situations require skills of the employees, such as social skills for teamwork and increased exchange with supervisors, methodological skills for problem-solving and unforeseen tasks and personal skills for learning in training and organising own tasks and timetables.

The regression result show that in principal, a stronger increase or a higher status of learning capacity tends to influence skill (mis-)match, an increase of tasks and the change of the occupational structure in a similar, sometimes even stronger way as the uptake of digital technologies. Especially, evidence could be found for hypotheses H4.1 ("*In sectors with a higher or growing learning capacity, employees are more likely to experience an increase in the number of their tasks* and H4.3 ("*In sectors with a higher or growing learning capacity, the change of the occupational structure is higher or growing.*"). With regard to H4.2 ("*In sectors with a higher or growing learning capacity, the mismatch of skills and tasks of their employees is higher or growing.*") not all possible effects in the regression steps proofed to be significant and the proportion of over-skilled employees was even negatively influenced by the learning capacity indicator. However, there was at least some (not very robust) tendency that a higher learning capacity is connected to a lower skill match.

The importance of the learning capacity / organisational level for individual properties of employees shifts the focus from the individual's responsibility of continuous upskilling and away from the techno-deterministic view of digitalisation to the companies' role in structuring jobs and the work environment. Putting employees' skills to good use for the company and harvesting the advantages of digital technologies, in terms of innovation and productivity increase, can be guided by the decisions companies make about the organisation of work in terms of division of tasks, teamwork, leadership styles, learning opportunities and the autonomy of workers.

The analysis has also shown that sectors with a high learning capacity and a high digital technology status are of particular importance. Represented by the interaction term, those sectors often had a weakening effect on the general effects of learning capacity and digital technologies. The strongest effects can be found within the regression on the proportion of over-skilled employees as well as the change of the occupational structure – in both cases, the effects of the main terms are weakened through the interaction term: there is less occupational restructuring and a higher proportion of employees that can perform more demanding duties. In these companies with a high innovative capacity, the technological transformation puts less pressure on the human resources.

Therefore, there is some evidence that at least a part of H4.4 (*"In Sectors with a higher or growing learning capacity and a higher or growing uptake of digital technologies, effects on the number of tasks, the (mis-)match of tasks and skills as well as the occupational structure will be reduced.")* is true.

5.5 Closing remarks on data and operationalisation

As described in the previous sections, only some of the hypotheses can be confirmed with the available data. This could be related to the fact that the assumed effects do not exist. Alternatively, they could be connected with the dataset's limitations, resulting in the lack of suitable, comprehensive underlying data sources.

In particular, when it comes to the more detailed assumptions, a number of improvements in the operationalisation of key concepts would help facilitate future research, as follows:

- Technological change can only be determined with predominantly IT, marketing and internet-related parameters. Many relevant technologies (for example, automation in production processes) are not included, so it wasn't easy to examine the effects on the prevalence of specific tasks.
- Structural changes of occupations, tasks and skills have been measured using the LFS and the EWCS which are employee level survey. We have not been able to include the EU wide Continuing Vocational Training Survey, which is an employer level survey, into our data strategy because of strong limitations in the data released by Eurostat for scientific purposes. Greenan and Napolitano (2022) provide further discussion of the data deficits in the digital age.
- The reference to specific organisations is limited by the "sector in countries" level. This aggregation does not allow analysing within sector heterogeneity.
- The limitation of the time dimension in the data also makes difficult to go further than a descriptive analysis.

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7. Annexes

Table A9 Operationalisation General increase of task and duties item.

Variables in the EWCS	Coding BEYOND 4.0 dataset
Q18d: "During the last 12 months has your work changed in any of the following ways?" "Your tasks and duties?" 1: Increased a lot 2: Increased a little 3: No change 4: Decreased a little 5: Decreased a lot	*tasks_increased* [answer options 1-2] *tasks_no_change* [answer options 3] *tasks_decreased* [answer option 4-5]

Note: Question codes as well as wording refer to the 2015 edition of the EWCS questionnaire (Eurofound, 2015a). 2010 wording only named when divergent (Eurofound, 2010). The coding is calculated for t0, t1 and the change of the value between t0 and t1.

Table A10 Operationalisation Skill mismatch item

Variables in the EWCS	Coding BEYOND 4.0 dataset
Q64: "Which of the following statements would best describe your skills in your own work?" 1: I need further training to cope well with my duties. 2: My present skills correspond well with my duties 3: I have the skills to cope with more demanding duties	*under-skilled* [answer option 1] *skill_match* [answer option 2] *over-skilled* [answer option 3]

Note: Question codes as well as wording refer to the 2015 edition of the EWCS questionnaire (Eurofound, 2015a). 2010 wording only named when divergent (Eurofound, 2010). The coding is calculated for t0, t1 and the change of the value between t0 and t1.

Table A11 Welfare state regime classification of countries

Social-Democratic	Southern	Liberal (Anglo-Saxon)	Conservative	Former USSR (Baltic)	Post-Communist
Finland	Greece	Ireland	France	Estonia	Croatia
Norway	Spain	United Kingdom	Austria	Lithuania	Hungary
Sweden	Italy		Luxembourg	Latvia	Poland
Denmark	Malta		Netherlands		Romania
	Portugal		Belgium		Slovenia
			Germany		Slovakia
					Bulgaria
					Czechia

Table A12 Used socio-democratic LFS variables

Variables in the LFS	Coding BEYOND 4.0 dataset
AGE	Proportion of young employees (aged between 15 and 29)
HATLEV1D	Proportion of employees with a high level of education (according to LFS)
SEX	Proportion of male workers in the sector-country-cells

Table A13 Correlation table Change of tasks (t_1), Technology Status (t_1) and Learning capacity (t_1)

	Task increased t_1	No change in tasks t_1	Task decreased t_1
Technology status t_1	0.30 ***	- 0.32 ***	0.02
Learning capacity indicator t_1	0.34 ***	- 0.35 ***	- 0.01

Note: All correlation estimates according to Pearson Correlation Coefficient s.: . - P ≤ 0.1 / * - P ≤ 0.05 / ** - P ≤ 0.01 / *** - P ≤ 0.001. — *Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

Table A14 Correlation table Skill (mis)match ($t_1 + \Delta t_{01}$), Technology Status ($t_1 + \Delta t_{01}$) and Learning capacity ($t_1 + \Delta t_{01}$)

	Under-skilled		Skill match		Over-skilled	
	t_1	Δt_{01}	t_1	Δt_{01}	t_1	Δt_{01}
Technology status t_1	0.23 ***	0.15 *	-0.19 **	-0.24 **	0.01	0.12 .
Technology status Δt_{01}	-0.06	- 0.05	-0.09	- 0.22 ***	0.15 *	0.21 ***
Learning capacity indicator t_1	0.32 ***	0.25 ***	- 0.23 ***	- 0.15 *	- 0.02	0.00
Learning capacity indicator Δt_{01}	0.06	0.24 ***	- 0.01	- 0.12 .	- 0.04	- 0.03

Note: All correlation estimates according to Pearson Correlation Coefficient s.: . - P ≤ 0.1 / * - P ≤ 0.05 / ** - P ≤ 0.01 / *** - P ≤ 0.001. — *Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

Table A15 Correlation table Overall ISCO change and single ISCO categories change (Δt_{01}), Technology Status (t_0) and Learning capacity (t0)

	Technology status t_0	Learning capacity indicator t_0
ISCO overall change indicator Δt_{01}	0.06	0.19 **
1. Managers Δt_{01}	- 0.04	0.03
2. Professionals Δt_{01}	0.22 ***	0.12 *
3. Technicians and associated professionals Δt_{01}	- 0.02	0.03
4. Clerical support workers Δt_{01}	- 0.14 *	-0.17 **
5. Service and sales workers Δt_{01}	0.06	0.07
6. Skilled agricultural, forestry and fishery workers Δt_{01}	- 0.03	- 0.00
7. Craft related trades workers Δt_{01}	- 0.05	- 0.04
8. Plant and machine operators, and assemblers Δt_{01}	- 0.05	0.04
9. Elementary occupations Δt_{01}	- 0.06	- 0.09
0. Armed forces occupations Δt_{01}	0.11 .	0.10 .

All correlation estimates according to Pearson Correlation Coefficient s.: . - P ≤ 0.1 / * - P ≤ 0.05 / ** - P ≤ 0.01 / *** - P ≤ 0.001. — *Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

Table A16 Regression of skill (mis-)match at t_0

		Under-skilled			Skill match t_0			Over-skilled t_0		
		B	Sig.	SE B	B	Sig.	SE B	B	Sig.	SE B
Step 1	Constant	- 0.03		0.04	0.69	***	0.06	0.34	***	0.06
	Digital technology indicator t_0	0.07		0.06	0.10		0.10	-0.15		0.10
	Learning Capacity indicator t_0	0.23	**	0.08	- 0.31	**	0.12	0.07		0.12
Step 2	Constant	- 0.12		0.15	0.68	**	0.23	0.30		0.23
	Digital technology indicator t_0	0.29		0.34	0.03		0.55	-0.05		0.53
	Learning Capacity indicator t_0	0.40		0.27	- 0.24		0.42	0.15		0.42
	IT Digital technology indicator : LC indicator t_0	-0.40		0.60	- 0.01		0.96	-0.18		0.93
Step 3	Constant	- 0.23		0.14	0.88	***	0.23	0.25		0.22
	Digital technology indicator t_0	0.34		0.33	- 0.14		0.54	0.01		0.52
	Learning Capacity indicator t_0	0.40		0.26	- 0.25		0.42	0.10		0.42
	Welfare Regimes: Southern	0.05	*	0.02	- 0.13	***	0.04	0.06		0.04
	Welfare Regimes: Liberal	0.00		0.03	- 0.17	***	0.05	0.15	***	0.04
	Welfare Regimes: Conservative	0.08	***	0.02	- 0.10	**	0.04	0.00		0.03
	Welfare Regimes: Former USSR (Baltic)	0.11	***	0.03	- 0.13	**	0.04	0.00		0.04
	Welfare Regimes: Post-communist	0.09	***	0.02	- 0.17	***	0.04	0.06		0.04
	IT Digital technology indicator : LC indicator t_0	- 0.30		0.58	- 0.06		0.94	-0.14		0.92
Step 4	Constant	- 0.15		0.15	0.80	***	0.24	0.26		0.23
	Digital technology indicator t_0	0.31		0.33	- 0.15		0.54	0.09		0.53
	Learning Capacity indicator t_0	0.39		0.26	- 0.23		0.41	0.15		0.42
	Welfare Regimes: Southern	0.04	.	0.02	- 0.10	**	0.04	0.04		0.04
	Welfare Regimes: Liberal	- 0.01		0.03	- 0.15	**	0.05	0.13	**	0.05
	Welfare Regimes: Conservative	0.07	**	0.02	- 0.08	*	0.04	-0.01		0.04
	Welfare Regimes: Former USSR (Baltic)	0.09	**	0.03	- 0.09	.	0.05	-0.03		0.05
	Welfare Regimes: Post-communist	0.08	**	0.02	- 0.14	***	0.04	0.03		0.04
	Share of high level of education t_0	0.06		0.04	- 0.14	*	0.07	0.10		0.07
	Share of male employees t_0	- 0.08	.	0.04	0.04		0.07	0.03		0.07
	Share of employees younger than 30 t_0	- 0.03		0.07	0.07		0.12	-0.08		0.11
	IT Digital technology indicator : LC indicator t_0	- 0.36		0.58	0.18		0.94	-0.43		0.94

Note: N=255 (one case was removed due to high Cooks' Distance value). Under-skilled Adj. R^2: Step 1: .06 / Step 2: .05 / Step 3: .14 / Step 4: .15 — Skill match Adj. R^2 Δt01: Step 1: .02 / Step 2: .01 / Step 3: .08 / Step 4: .09 — Over-skilled Adj. R^2 Δt01: Step 1: .00 / Step 2: .00 / Step 3: .05 / Step 4: .05 — *Source: Beyond 4.0 integrated database CIS-CICT-ECWS-LFS — Coverage: EU27 plus UK and Norway, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors C, F to N.*

PART C - TASK 5.5
TECHNOLOGICAL TRANSFORMATION, QUALITY OF WORK AND OCCUPATIONAL RISKS

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Deliverable type version: D5.1 – May 2023
Associated Work Package: WP5
Lead: CNAM-CEET
WP leader: Nathalie Greenan

Document Summary

Document type:	*Deliverable D5.1 – Part C*
Title:	Technological transformation, quality of work and occupational risks.
Author/s:	*Gerben Hulsegge, Irene Houtman, Iris Eekhout, Marjolein Douwes & Coen van Gulijk*
Reviewer/s:	*Nathalie Greenan, Silvia Napolitano, Peter Oeij*
Date:	*March 24, 2023*
Document status:	*Final*

Abstract

This report describes the joint analysis of five EU-wide datasets to assess the relationship between the digital transformation, and quality of work and occupational risks. We focus on psychosocial risks, physical working conditions and environmental risks in the workplace. Structural Equation Models were used to analyse the relationship between technological inputs, and quality of work and occupational risks, and also to test the mediating role of innovation outputs and supportive organisational practices. We found that overall R&D investments and digital technology adoption and use were related with better quality of work and less occupational risks. Some of the relationships between technological inputs and outcomes for quality of work and less occupational risks were mediated by supportive organisational practices and innovation indicators. The introduction of both technological and non-technological innovations was associated with more physical workload and less environmental risks at the workplace and less sitting. We also found that having self-managing teams, formal employee representation and ways to discuss health & safety issues within teams have beneficial effects on psychosocial, physical and environmental risks in the workplace when developing new knowledge or using digital technologies.

Content

Executive summary

This report investigates the links between digital technologies and investments in new knowledge as the inputs of the technological transformation on quality of work and occupational risks. The role of technological and non-technological innovation as well as supportive organisational practices are also considered.

Technological transformation within organisations must be considered as interdependent with organisational changes as well as changes in the industry, region, country and EU. Technological transformation can be seen as a relationship between investments (in R&D, technology, the organisation) and innovations. Thus, if tasks are changed in a certain direction, it is because companies have decided to use technological or organisational opportunities in a certain way. Such choices have consequences for quality of work and occupational risks because the change process itself can disturb previous equilibria between demands and resources, and can either improve or deteriorate employee level outcomes.

This report is part of a Beyond 4.0 deliverable on the socio-economic consequences of technological transformation, and specifically aims to investigate the relationship of the new knowledge and (digital) technologies with quality of work and occupational risks. We focus on psychosocial risks, physical working conditions and environmental risks in the workplace. The BEYOND 4.0 dataset is used in which variables from several European survey data sources are combined at the sectoral level in countries, where the individual values represent shares or scores within these country-sector cells.

Our results imply that investments in new knowledge and (digital) technology has more favourable than unfavourable effects regarding better quality of work and less occupational risks. We observed that investments in new knowledge and (digital) technology was directly related to less emotional job demands, more autonomy, less lifting heavy loads, less working in tiring positions, less repetitive work and less environmental risks at the workplace, but with more sitting at work and no relation with psychological job demands. These were mainly direct effects of technology on quality of work and occupational risks, irrespective of innovation indicators and supportive organisational practices.

However, innovation and employee involvement did play a role for some outcomes. The introduction of technological and non-technological innovations was associated with more physical workload and less other workplace environmental occupational risks. This implies that pro-active policies at the company level are needed to mitigate the effect of such innovations on physical workload. The impact of investments in new knowledge and use of digital technologies on psychosocial risks was mediated by some forms of employee involvement. In particular, we found that having self-managing teams, formal employee representation and forms to discuss health & safety issues with teams have a beneficial effect on psychosocial and physical risks and reduce environmental risks at the workplace. These findings highlight the importance of human-centered design principles and a high-road company strategy, such as workplace innovation and psychosocial risk management, in organisations that work with or introduce new technologies.

1 Introduction

The world of work is changing. Main drivers are globalisation, political and demographic changes, and major technological changes through digital transformation in Industry 4.0. In Beyond 4.0, we define Industry 4.0 as a specific form of technological transformation. With the digitisation of production through the use of computers, artificial intelligence (AI) and automation/robotics, both physical (manual) tasks and, increasingly, some cognitive (mental) tasks currently performed by humans can be automated (Warhurst et al., 2019: D2.1). Technology is, however, not deterministic. Instead, strategic choices are the central drivers of change. Technological transformation within organisations must be considered as interdependent with organisational changes as well as changes in the industry, region, country and EU (Berting, 1993; Bijker et al., 2012; Child, 1972; Greenan & Napolitano, 2021, Noble, 1984). Technological transformation can be seen as a relationship between investments (in R&D, technology, the organisation) and innovations. Thus, if tasks are changed in a certain direction, it is because companies have decided to use technological or organisational opportunities in a certain way. Such choices have consequences for quality of work and occupational risks because the change process itself can disturb previous equilibria between demands and resources, and can either improve or deteriorate employee level outcomes.

The scientific debate about the relationship between technology on the one hand, and quality of work and occupational risks on the other, leads to the notion that (1) job design has a central position, (2) there is need for explicitly considering human-centered design principles in the development of these new technologies, (3) these organisational-level implementations (or intervention) strategies need to be supported by macro-level policies, and (4) education and training of individuals remain important, although there is a need to go beyond a focus on upskilling employees to help them adapt to technology change, to also focus on training employees, as well as other stakeholders, in work design and related topics (Parker & Grote, 2020). Demerouti (2020) adds to this discourse by debating that digitalisation and automation can contribute to stimulating 'healthy' jobs if (1) they are designed to support people's work, (2) people are in control and can craft their use, (3) job resources are maximised and job demands are affordable, (4) the economic growth is shared among stakeholders, including employees, and (5) authorities protect employees and employment conditions.

Currently, literature on the impact of the technological transformation on quality of work and occupational risks is limited. A common assumption is that the technological transformation results in less demanding physical working conditions (e.g. lifting heavy loads), but to more sitting at work and more psychological risks (Bisello, 2019; Karimikia et al. 2020; Marsh et al., 2022). However, as discussed above this is likely to depend on strategic choices of companies. The technological transformation might in high-road companies - that provide a supportive work environment where employees have a voice and technological investments are chosen and implemented based on humanistic values - have better employee level outcomes related to quality of work and occupational risks. There is lack of cross-country EU-wide analysis on the relationship between technological transformation, and quality of work and occupational risks, and little is known on how innovation and supportive organisational practices including employee involvement influence these relationships. More insight into factors that can positively influence the impact of technological transformation on quality of work and occupational risks is helpful for the development of policies that enhance optimal implementation and use of (digital) technologies that eventually contribute to productivity and employee health and safety.

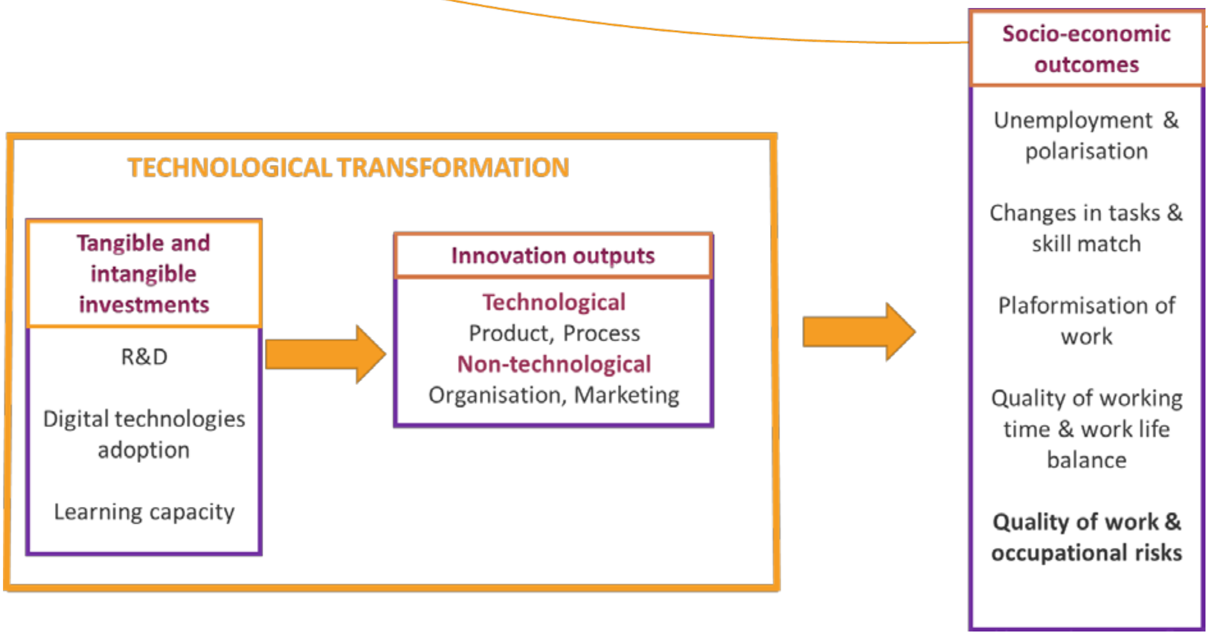
WP5 of Beyond 4.0 aims to analyse the socio-economic consequences of technological transformation through taking stock on the existing empirical literature and using the datasets prepared in WP3. It strives to make inferences based on EU-wide datasets on the relationships between technological transformation on a range of outcomes. This report is part of a series of reports on this topic, and specifically aims to investigate the relationship of the new knowledge and (digital) technologies with quality of work and occupational risks. We focus on psychosocial risks, physical working conditions and environmental risks in the workplace. Report of T5.4 reports on related outcomes, including work-life balance and working time autonomy.

2 The theoretical framework

In report D3.2, Greenan et al. (2023) present a theoretical framework to gain insight into the impact of the technological transformation on socio-economic outcomes. This framework presented in Figure 1 starts with the notion that there are complementarities and interdependencies among technological and organisational changes. We consider that technology is not deterministic, but that technological transformation within organisations is interdependent with organisational changes as well as changes in the industry, region, country and EU (Berting, 1993; Bijker et al., 2012; Child, 1972; Noble, 1984). The way organisations are designed, their organisational structure and the organisation of work is crucial to understand both organisational performance and (employee) outcomes in terms of socio-economic outcomes. As mentioned, in this chapter, we focus on quality of work and occupational risks.

With quality of work or quality of the working environment, we mean the properties of work itself that captures non-economic aspects of employment (Cazes, Hijzen & Saint-Martin, 2015). It is a multi-dimensional construct, made-up of interrelated factors and concern the completeness of the tasks (coherent set of preparatory, executive and supporting tasks), variation and challenge in work, autonomy, physical, psychological and environmental risk factors in the workplace. An important aspect of the quality of work is the balance between control options and control requirements of the work. Control options refer in particular to autonomy in work, and the possibility to ask for help from colleagues (internal and external control options); control requirements refer to the qualitative and quantitative standards of work performance (the quantity, the quality, deadlines, lead time, physical workload). If control options and control requirements are in balance, the worker can solve any control problems in a healthy, safe and productive way. There are also views on ‘quality of work' which cover all occupational risks as well as working relations at work (e.g. Cazes, Hijzen & Saint-Martin, 2015). The latter approach is too broad for this report, where we will deal with occupational risks that refer to all psychosocial, physical and environmental risk factors in the workplace. Occupational risks may cause injury or illness of both physical as well as mental nature. Environmental risks are restricted to risks such as exposure to noise, high temperatures and chemicals in the workplace.

Figure 1. The theoretical framework considering the impact of technological inputs on innovation outputs and socio-economic outcomes.



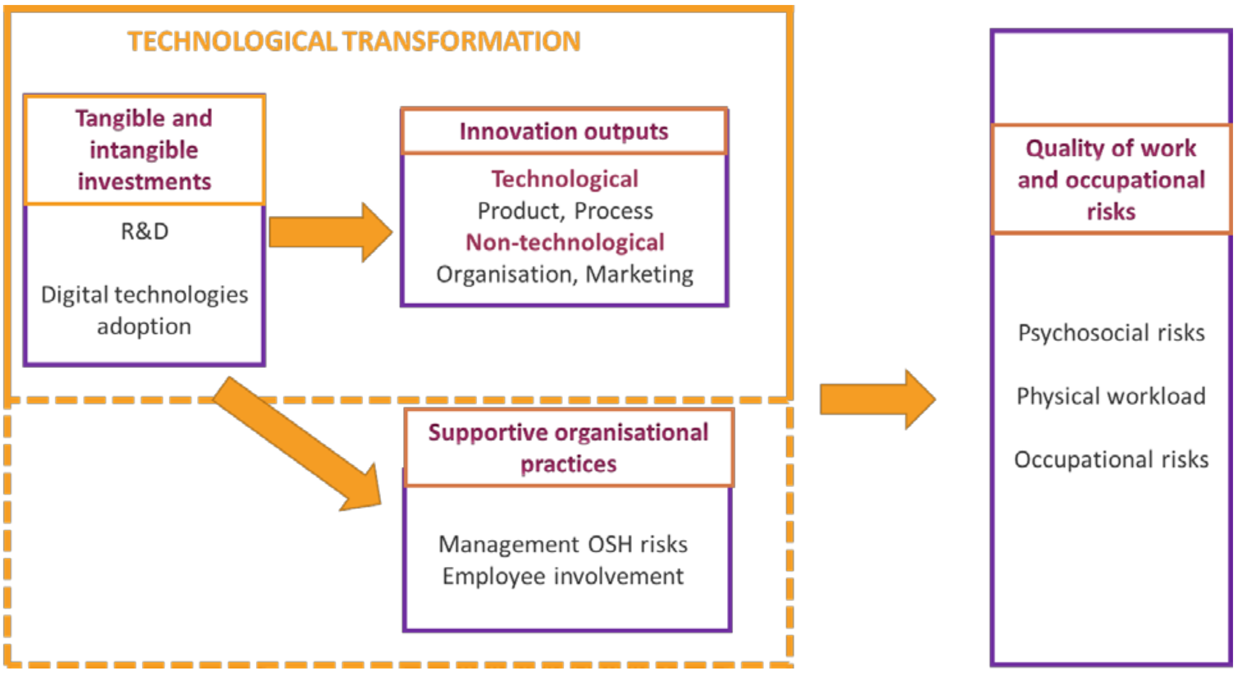
Company strategies are central drivers of change, and they may largely vary from one organisation to another. Both innovators and followers produce by investing in some technological inputs that can either be tangible or intangible investments. Until about 15 years, investments were primarily on tangible technology, such as automatisation and computerisation (Haskel & Westlake, 2018). Currently, companies are more and more investing in intangibles including patents and self-developed software. We distinguish three investments in new knowledge: R&D investments, digital technologies adoption and use and learning capacity of the organisation. We view the technological transformation, not only as the inclusion of digital technologies into the production process but also as a relationship embedded in the production process, sometimes called the knowledge production function. It relates technological inputs in which companies invest with innovation outputs. Digital technologies are one of these inputs, together with R&D expenditures. The learning capacity of an organisation is its ability to adapt and compete at low cost through learning (Greenan and Napolitano, 2023). It is related to the skills, management tools and organisational practices that support individual and organisational learning. In our framework, we suggest that R&D, digital technology adoption and learning capacity of the organisation inputs are transformed into innovation outputs (technological (product/process) and non-technological (marketing or organisational) innovation), which in turn may affect quality of work and occupational risks.

For this chapter, we have adapted the framework of Greenan et al. (2023) (Figure 2). We have not included the learning capacity of the organisation in our model as 1) we consider autonomy as an outcome of the technological transformation whereas autonomy in cognitive tasks and autonomous teamwork are components of the 'learning capacity' concept.. A 'learning' organisation needs autonomy, however, this autonomy has to be perceived as such by employees to have a moderating effect on. the demands at work. It is therefore important to note that in our operationalisation of the autonomy concept we use employee reports on and thus their perception of autonomy in their work. In addition, (2) the available datasets we were able to use have constraints and insufficient data to construct the learning capacity indicator at the organisational level (see Methods and data section).

We do consider instead the role of different supportive organisational practices that are of importance in relation to the quality of work and occupational risks. Some of these supportive organisational practices, such as autonomous teamwork and employee involvement in relation to the quality of work and social dialogue are also part of the learning capacity indicator. We argue that some specific supportive organisational practices like employee participation and the discussion on quality of work like on psychosocial risks and other occupational risks will protect workers safety and health in relation to the technological transformation.

Parker (2020) argues that work design is a valuable perspective for understanding the effects of new technology. Research addressing workplace innovation (e.g. Oeij et al, 2017; Oeij et al, 2019), and psychosocial and musculoskeletal risk management (e.g. Nielsen & Randall, 2013; Westgaard & Winkel, 2011), suggests that the impact of demands, as well as the way organisations deal with (technological) change is mediated by employee involvement. Our framework implies that the impact of technological transformation on quality of work and occupational risks is mediated by supportive organisational practices including the degree of employee involvement, proper communication and management commitment to worker health and the way occupational health & safety risks are managed (lower part of Figure 2). We discuss this in more detail in the sections below.

Figure 2. The theoretical framework considering the impact of new knowledge and (digital) technologies on the employee level outcomes of occupational risks and quality of work via innovation outputs and supportive organisational practices. Abbreviation: OSH: occupational safety & health.



3 Relation between the technological transformation, and quality of work and occupational risks

3.1 Technological transformation and psychosocial risks

Psychosocial risks relate to the demands imposed by work. In general, demands may be quite diverse and may relate to quantitative, as well as cognitive or emotional demands, or even physical demands (Houtman et al, 2020), but its impact is alleviated by aspects of control, like having control over time and place during which or where the demands have to be delivered. The moderating and/or mediating effect of autonomy in relation to time and place as well as of support from supervisors and co-workers have substantially been described (e.g. Karasek, Triantis & Chaudhry, 1982; Karasek & Theorell, 1990). Psychosocial risks have been increasing in Europe at the start of the century (Greene & McIntosh, 2001). However, on an average basis, this could not be identified as an increasing risk in all EU-countries, as was the case in some countries, like in The Netherlands (Houtman et al, 2020; Houtman et al, 2017). On the other hand, the increase in psychosocial risks may have occurred in certain sectors, or for certain risk groups.

The 'Demand-Control' (DC) model (Karasek & Theorell, 1990) has stimulated many studies on work, particularly on psychosocial risks at work, and health and wellbeing. These studies often support main effects and sometimes moderating effects of indicators of job control on demands at work with wellbeing, health or sickness absence as outcomes (e.g. Häusser et al., 2010). The DC- model focusses on the balance between psychological work demands, such as time pressure, and having job control. High job demands in combination with high control leads to active jobs, with motivated employees and learning opportunities, while a lack of control leads to a higher risk of work-related stress or job strain. The DC-model enables the exploration of the dual role of digitalisation as both a demand and a resource in relation to work-related stress and job strain (Marsh et al., 2022).

Literature on the relationship between (digital) technology and psychosocial risks is yet contradictory. Bisello (2019) found no effect of computerization in the EWCS on job autonomy, while other studies found that monitoring tasks, pace and outcomes gives employees less room to make meaningful and substantive decisions about their work (Das et al., 2020; Stefano, 2019). The review of Karimikia et al. (2020) found that autonomy exacerbated the effects of ICT use resulting in more work-related stress. With regard to quantitative or psychological job demands, most studies observed that demands increase due to technology. On the one hand, technology may drive high pace of work and reinforce pressure to increase productivity, increase unpredictably of demands, and adoption of new technologies and excessive use of ICT-tools (Marsh et al., 2022; Yin et al., 2018). On the other hand, technology and ICT tools can also increase flexible working (e.g. flexible time and place of working) or could act as job crafting tools for designing work tasks and promoting individual job resources (Bakker & Demerouti, 2014).

Based on inconsistent previous findings on the relationship between digital technology and psychosocial risks and the lack of literature on the relationship with investments in new knowledge, it is yet unclear whether the technological transformation relates to more or less psychosocial risks in the EU. We do hypothesise that technological and non-technological innovations and supportive organisational practices (partly) mediate the relationship between investments in new knowledge and (digital) technology on less psychosocial risks.

3.2 Technological transformation and physical working conditions

Krause & Douwes (2019) studied the effect of *digitalisation* on working conditions in the Netherlands in both the literature and through qualitative case studies. *Automatisation* was found to have an effect on several aspects of the working conditions. Whether these effects are positive or negative depends largely on the type of technology and the context or specific application, since the tasks that are not taken over by automatisation determine the working conditions after implementation. In general, automatisation often seems to reduce heavy physical workload (heavy manual lifting, pushing and pulling, as can be seen in the logistics sector), working in vibrating vehicles (forklifts) or with vibrating tools, and precision work (cobots). Automatisation and computers may also replace routine-based tasks, while creative and social tasks cannot be so easily replaced by computerization (Bisello et al., 2019; Krause & Douwes, 2019; Stacey et al., 2018). However, the results of Bisello et al. (2019) also show that computer work is significantly reducing social tasks and increasing repetition and standardisation of work.

Digitalisation of work in general is associated with an increase of computer work. The percentage of people in Europe working with computers, laptops or keyboards for all or almost all of the time increased from 17.6 % in 2000 to 30.3 % in 2015 (Eurofound, 2017). Computer use is associated with the augmented risk of *Repetitive Strain Injuries* (RSI) (Van Tulder, Malmivaara & Koes, 2007). The use of laptops and smartphones may even strengthen this effect (Dennerlein, 2015). Moreover, the increase of computer use has been suggested as the main reason for the apparent increase in *sitting at work* over the last decades. In the 2019 European Survey of Enterprises on New and Emerging Risks (ESENER), the second most frequently reported risk factor in the EU-27 (61 % of establishments) was prolonged sitting (EU OSHA, 2019). According to the 2015 EWCS (Eurofound, 2017), 28% of workers report sitting at work almost all the time and 30% report sitting a quarter to three-quarters of the time.

A foresight study by EU OSHA (Stacey et al., 2018) presented an overview of the expected impact of ICT on occupational safety and health. Effects that they expected with regard to physical workload are:

- a reduction of manual handling: collaborative robots can take manual handling tasks away from workers.
- an increase of repetitive work: while offering OSH benefits to many workers by removing them from exposure to hazardous environments, automation could either leave workers with highly repetitive tasks, with the robot determining the rate at which the tasks are carried out, or with highly difficult and/or dangerous tasks, and reduce the scope for task rotation and variety.
- an increase in sitting at work and a reduction of physical activity, stemming from an increase of ICT/online work, as this work is, in general, done while sitting (although sit-stand desks can be used). Work processes can be controlled, monitored and also increasingly maintained remotely, removing the physical activity associated with attending them in person. ICT-enabled technologies (ICT-ETs) also enable working from home (teleworking), which removes the physical activity in commuting to and from work, as well.

We hypothesise the following based on the literature results above:

- Digital technology is related to a reduction of lifting heavy loads and working in tiring positions.
- Digital technology can either be related to less or more repetitive work (among others depending on the division of work tasks between robot and workers.
- Digital technology is related to increased total duration of sitting at work.
- As we know little about the relationship between investments in new knowledge and physical working conditions, new knowledge can either reduce, increase or have no effect on lifting heavy loads, working in tiring positions, repetitive work and sitting at work.
- Technological and non-technological innovations and supportive organisational practices (partly) mediate the relationship between investments in new knowledge and (digital) technology on less demanding physical working conditions.

3.3 Technological transformation and environmental risks at the workplace

Working with digital technologies such as collaborative robots, ICT technology and Artificial Intelligence (AI), changes the way humans interact with machines. This change induces changing safety risks and potentially alters the numbers of incidents. The EU has recognised that such novel technologies require additional safety assurances. Especially the proposal for the revision of key safety legislation in the field of AI. Most central to such changes is the Machine Directive (Directive 2006/42/EC of the European Parliament and the council of 17 May 2006 on machinery, and amending Directive 95/16/EC). That regulation stipulates that extensive risk analyses need to be made before the machine can be put on the European market and used by workers. The directive has suggested in the proposal for a regulation of machinery products by the European Parliament. The regulation modernises the machine directive by incorporating concerns relating to digital systems and AI. At the same time, it elevates the law from a directive, which needs to be transferred to national legislation, to a regulation, which is applicable without national intervention.

Central to EU legislation is that risk analyses have to be made for workplace environments and machines with which a person interacts. With newer, smarter machines in the workplace, the risk analysis changes by default. When there are high levels of exposure to machines, it is legally obligatory to provide prevention measures. The nature of these measures depends on the many different ways that a machine can cause harm to a person. Traditional programmable industry robots (e.g. welding robots) are considered so dangerous that they have to be put in cages in places where people work; no one is allowed near them whilst they are operating and fencing ensures that cannot happen. Nevertheless, modern flexible robots and cobots are lighter, perform less dangerous jobs (such as order picking) and are equipped with elaborate safety functions. Such robots are allowed to share the working space with humans but only after elaborate safety studies are performed. The actual exposure to harm may be relatively small but the nature of the workplace environmental risk will have changed considerably when compared to a shielded robot.

The EU OSHA (Stacey et al., 2018) study indicate that automation, virtual reality (VR) for training purposes, robotics and autonomous vehicles or drones (Busick, 2016; Katwala, 2017) can reduce the need for workers to work in hazardous environments such as exposure to noise and substances or to come into contact with moving machinery. However, the same technologies could be a source of harm, through trapping, entanglement, noise and vibration, should anyone work alongside them, for example in the case of collaborative robots (Steijn, et al., 2016) or bionic exoskeletons.

Based on inconsistent findings and limited literature on the relationship between digital technology and workplace environmental risks and the lack of literature on the relationship with investments in new knowledge, it is yet unclear whether the technological transformation relates to more or less workplace environmental risks in the EU. We do hypothesise that technological and non-technological innovations and supportive organisational practices (partly) mediate the relationship between investments in new knowledge and (digital) technology on workplace environmental risks.

4 Methods and data

4.1 Datasets

Our secondary analysis builds on the construction of cross-country and cross-sector existing datasets that are based on the integration of EU wide surveys that allow exploring the relations between company level decisions and employee level outcomes (Greenan et al., 2023). The most recent EU-wide dataset for employees with reliable and valid measurements of quality of work and occupational risks is the European Working Conditions Survey (EWCS, Eurofound) from 2015. We were, therefore restricted to perform analyses on EU-wide data gathered in 2015 or before. Our data covered a maximum of 28 countries (the EU 27 Member States, plus the UK) and 15 industries (the NACE Rev. 2 at 1-digit level, sections B to N and R and S) from data gathered in 2013, 2014 and 2015. Our data integrates information from four EU-wide employer level surveys with the EWCS, taking advantage of the richness of having multiple different and complementary sources that cover different aspects of our theoretical framework. The employer level surveys used cover organisations with more than 10 employees.

The first employer level dataset is the **European Company Surveys (ECS) 2013**, which is a questionnaire-based representative sample survey of business establishments with at least 10 employees. Interviews took place with the manager responsible for human resources in the establishment. The survey focusses on work organisation, workplace innovation, HR practices, employee participation and social dialogue. We gathered data about new knowledge including the design of products and services at the establishment and the monitoring of external ideas and technological developments.

The second organisational level source is the **Community ICT usage and e-commerce in enterprises (CICT) (Eurostat) 2014**, which yearly provides direct measures on the use of Information and Communication Technologies and e-commerce in European organisations. It is a central survey to measure the digital revolution. Because of confidentiality issues, Eurostat releases only the aggregated data at the country and sector level. The ICT usage includes less sectors than the other questionnaires and lacks, for example, the services sectors including public services and health care. We gathered data about the adoption rates, at the country-sector-year level as well as at the European level, of several specific technologies and we constructed a composite indicator of technology adoption and use.

The third organisational level source is the **Community Innovation Survey (CIS, Eurostat) 2014**, carried out every two years. It provides information on different types of innovation outputs, defined on the basis of the conceptualisation provided by the Oslo Manual (OECD/Eurostat, 2005), as well as on various aspects concerning the companies' innovation activity, such as the cooperation with other organisations or the provision of public funding. We used the CIS to identify R&D expenditures.

The fourth organisational level source is the EU-OSHA's **European Survey of Enterprises on New and Emerging Risks (ESENER-2) survey 2014** that investigated how safety and health risks were managed in the workplace, with a particular focus on psychosocial, physical and environmental risks at work. Although enterprises with at least five employees were covered in this survey, we homogenised the sample using only enterprises with ten or more employees. On average, our dataset included about 1,400 establishments per country. For ESENER-2, data were collected at the organisational level by means of telephone interviews with the person 'who is best informed about OSH issues'. In small and medium-sized organisations, this was mostly the owner/director, but in larger organisations, it was an OSH specialist (such as a health and safety officer) or a safety manager.

The fifth source is the **European Working Conditions Survey** (**EWCS, Eurofound) 2015**, which is targeted to employees. The EWCS assesses the workers' experience with physical and psychosocial risk factors, working time, psychological job demands, employee participation, skills and development, employment condition, social relations at work, gender issues and well-being and health. We used data on quality of work and occupational risks outcomes.

Combining the data

These five surveys are combined using a "common cell" constructed using key variables, which for our analyses are 'country' and 'sector. For each technological input variable (R&D and technology adoption and use), we analysed separate models (see data analysis section 4.3). As the country and sector coverage differs according to the survey used, we constructed three merged datasets with differing number of country-sector cells:

1) ECS, ESENER, EWCS; EU27+UK, 15 sectors (NACE Rev. 2 1-digit sectors B to N, R and S)

2) CIS, ECS, ESENER, EWCS; EU27+UK, 13 sectors (NACE Rev. 2 1-digit sectors B to N)

3) CICT, ECS, ESENER, EWCS; EU27+UK, 10 sectors (NACE Rev. 2 1-digit sectors C, F to N)

Differences in number of observations when reporting on the analyses are mostly caused by the specific country and sector coverage of the surveys joined, generating different missing cells. Especially the third dataset has limited sector coverage and small sample size (see also paragraph 4.3).

4.2 Operationalisation of variables

Technological input variables

Table 1 provides a summary of the technological input variables deducted from three surveys (ECS, CIS, and CICT). R&D expenditures (in house or external, continuous or occasional) are an indicator at the input side of intangible investments, and related investments to create new knowledge and applications for intellectual property rights and licensing (patents, European utility model, industrial design rights, trademarks) as well as investments for the acquisition of intellectual property and knowledge from other organisations, including universities and research institutes.

Table 1. Overview of the measured technological input variables.

<table>
<tr><th></th><th>Dataset</th><th>Variable name</th><th colspan="2">Description</th></tr>
<tr><td rowspan="3">New knowledge</td><td>ECS</td><td>Design products & services</td><td colspan="2">Design or development of new products or services carried out at the establishment of the organisation in 2013 (range: 0-1; higher score is more R&D activities)</td></tr>
<tr><td>ECS</td><td>Monitoring external developments</td><td colspan="2">Establishment monitors external ideas or technological developments for new or changed products, processes or services in 2013 (range: 1-3; higher score is more serious following developments)</td></tr>
<tr><td>CIS</td><td>In-house R&D</td><td colspan="2">In-house R&D engagement (expenditures including labour costs and capital expenditures on buildings and equipment specifically for R&D) between 2012 and 2014 (range: 0-1; higher score is more R&D activities)</td></tr>
<tr><td rowspan="5">Digital technology adoption and use</td><td rowspan="5">Community ICT usage and e-commerce in enterprises (CICT)</td><td rowspan="5">(range 0-1; higher score = more digital technology adoption)</td><td>E-commerce</td><td>Enterprises purchasing online; E-commerce sale (web sales) in 2014</td></tr>
<tr><td>Connection technologies</td><td>Access to the Internet; Fixed broadband access; Mobile broadband connection in 2014</td></tr>
<tr><td>Web and Social media technologies</td><td>Website or Home Page; Use social networks (e.g. Facebook, LinkedIn, Xing, Yammer, etc.) in 2014</td></tr>
<tr><td>E-business technologies</td><td>ERP (Enterprise Resource planning) software package to share information between different functional areas; Customer Relationship Management (CRM) in 2014</td></tr>
<tr><td>Cloud computing</td><td>High CC services (accounting software applications, CRM software, computing power); Medium CC services (e-mail, office software, storage of files, hosting of the enterprise's database) in 2014</td></tr>
</table>

This is measured in the ECS as design of products & service and the monitoring of external ideas and technological developments, and in the CIS as in-house R&D expenditures. We also refer to these R&D investments as 'new knowledge'.

The Digital technology adoption and use indicator is based on information from the CICT. Four basic technologies (E-commerce, Connection technologies, Web and Social media technologies and E-business technologies), and one advanced technology (cloud computing) are considered. There are several underlying item for each basic or advanced digital technology as presented in table 1. The overall indicator takes into account both the use and the novelty of each item: the percentage of enterprises that use the corresponding technology in a given industry within a country is weighted by the inverse of the European diffusion rate for each technology in 2010, which proxies its technological intensity. In so doing, those technologies that are reaching their exhaustion point have lower weights, while emerging technologies have higher ones. This overall indicator sums up the weighted share and it is then standardised leading to a range from 0 to 1. More details about the operationalisation of variables can also be found in Greenan et al. (2023).

Output and mediating factors

Table 2 provides a summary of the output variables and supportive organisational practices from three surveys (ECS, EWCS, and ESENER).

In line with the notion provided by the Oslo Manual (OECD/Eurostat, 2015), statistical surveys generally define innovation as the introduction of a new or significantly improved product, process, organisational or marketing method by an organisation. An innovation needs only to be new or significantly improved for the organisation (but not necessarily new to the market) or originally developed or used. We distinguish two forms of innovation: technological innovation in product or process, and non-technological innovation in marketing or organisational. We consider the company level combination of these four types of innovation and retain three innovation indicators: technological innovation only, non-technological only, technological and non-technological innovation.

Four different supportive organisational practices concerning the involvement and participation of employees were measured:

- The use of autonomous teamwork;
- The degree of formal employee representation in trade union, health and safety delegate or committee, and regular formal meetings with employees (Cronbach alpha: 0.65)
- The degree health and safety issues are discussed with staff and teams
- The degree employees are involved in implementing health & safety measures

With regard to OSH risk management, managing general OSH risks and managing psychosocial risks were differentiated and either used to mediate physical or environmental risks as outcomes or psychosocial risks as outcomes:

- The absence of barriers related to implementing OSH measures including having sufficient time, money and expertise (Cronbach alpha: 0.73)

- The absence of difficulties in addressing PSR risks including awareness of staff and management (Cronbach alpha: 0.73)

Table 2. Overview of the measured innovation outputs and supportive organisational practices.

	Dataset	Variable name	Description
Innovation	ECS	Technological and non-technological innovation	New or significantly changed products OR process AND organisation OR marketing between 2010 and 2013 (range: 0-1, higher score is more innovation)
		Non-technological innovation only	New or significantly changed organisation OR marketing ONLY between 2010 and 2013 (range: 0-1, higher score is more innovation)
		Technological innovation only	New or significantly changed products OR processes ONLY between 2010 and 2013 (range: 0-1, higher score is more innovation)
Supportive organisational practices	ECS	Autonomous teamwork	Team members can decide among themselves by whom tasks are to be performed vs no teams present or tasks are being distributed by a superior in 2013 (range: 0-1; higher score identifies autonomous teamwork)
		Formal employee representation	Presence of trade union, works council or similar committee representing employees; presence of health and safety delegate or committee; regular meeting in which employees can express their views about what is happening in the organisation (range: 0-3, higher score is more employee representation)
	ESENER	Discussion health & safety issues	Are health and safety issues regularly discussed in staff or team meetings in 2014? (range: 0-1, higher score is more discussion)
		Employee involvement OSH measures	If measures have to be taken following a risk assessment: are the employees usually involved in their design and implementation in 2014? (range: 0-1, higher score is more employee involvement)
		OSH risk management	Sufficient time/staff, money, awareness among staff/management, expertise, and no issues regarding paperwork and complexity of legal obligations in 2014 (range: 0-6, higher score is better OSH risk management)
		PSR risk management	No difficulties in addressing PSR risks including awareness staff and management, specialist support, no reluctance to talk openly) in 2014 (range: 0-4, higher score is better PSR risk management)

Outcomes

Table 3 provides a summary of the outcome variables from the EWCS. The variable 'emotional job demands' was constructed from two items indicating the degree the job involves handling angry clients/customers/patients and being in situations that are emotionally disturbing (correlation=0.47). Psychological demands was the average on two items indicating high work speed and tight deadlines (Cronbach alpha=0.78). Autonomy was measured using three items on control over order of tasks, work method and work speed (Cronbach alpha = 0.77). Lifting heavy loads was measured using one item indicating the amount of time at work carrying or moving heavy loads. Working in tiring positions was measured using one item indicating the time an employee spends in tiring or painful positions. Repetitive work was a single item question on whether work involves short repetitive tasks of less than one minute. Sitting was also a single item question on the amount of worktime one spends sitting. Environmental risks at the workplace were measured using nine different items, covering different occupational environmental risks (see table 3; Alpha=0.82). This measure of environmental risks was significantly correlated with both fatal (r=0.40) and non-fatal (r=0.42) registered occupational accidents (register data from Eurostat by country and sector).

Table 3. Overview of the measured quality of work and occupational risks outcomes from the EWCS.

Outcomes	Variable name	Description
Psychosocial risks	Emotional job demands	Angry clients/customers/patients, being in emotionally disturbing situation in 2015 (range: 0-4, higher score is more demands)
	Psychological job demands	High work speed, tight deadlines in 2015 (range: 0-14, higher score is more demands)
	Low autonomy	Control order tasks, method of work, speed and rate of work in 2015 (range: 0-3, higher score is less autonomy)
Physical working conditions	Lifting heavy loads	Time spent working lifting heavy loads in 2015 (range: 0-1, higher score is more lifting heavy loads)
	Working in tiring positions	Time spent working in tiring positions in 2015 (range: 0-7, higher score is more tiring positions)
	Repetitive work	Presence of tasks less than 1 minute in 2015 (range: 0-1, higher score is more repetitive work)
	Sitting	Amount of time sitting during a work day in 2015 (range: 0-6 higher score is more sitting)
Workplace environmental risks	Workplace environmental risks	Vibration, noise, temperature, fumes, vapours, chemical, tobacco, infectious materials in 2015 (range: 0-36, higher score is more occupational risks)

Confounders

Sector was dichotomised into production (NACE Rev. 2 at 1-digit level, sections B-F) and services sectors (NACE Rev. 2 at 1-digit level, sections G-N, R, and S). We used the average and SD of company size. Region was categorised into West, North, South and East EU.

4.3 Data analyses

To analyse jointly the data from surveys addressed to employees and to employers that we cannot link directly, all variables from the different data sets were averaged at the level of sector within country cells. The country and sector variables that are key in this data integration process have been recoded and relabelled to have the same names and format in all datasets. When the survey was available at the individual level (I.e. EWCS, ECS and ESENER), the micro data was aggregated by computing a weighted mean in each subcategory. The data from CIS and CICT were aggregated by Eurostat. The data from the various sources were finally merged by the common aggregate levels (i.e., a sector within a country).

In analysing the data, we performed the following five steps:

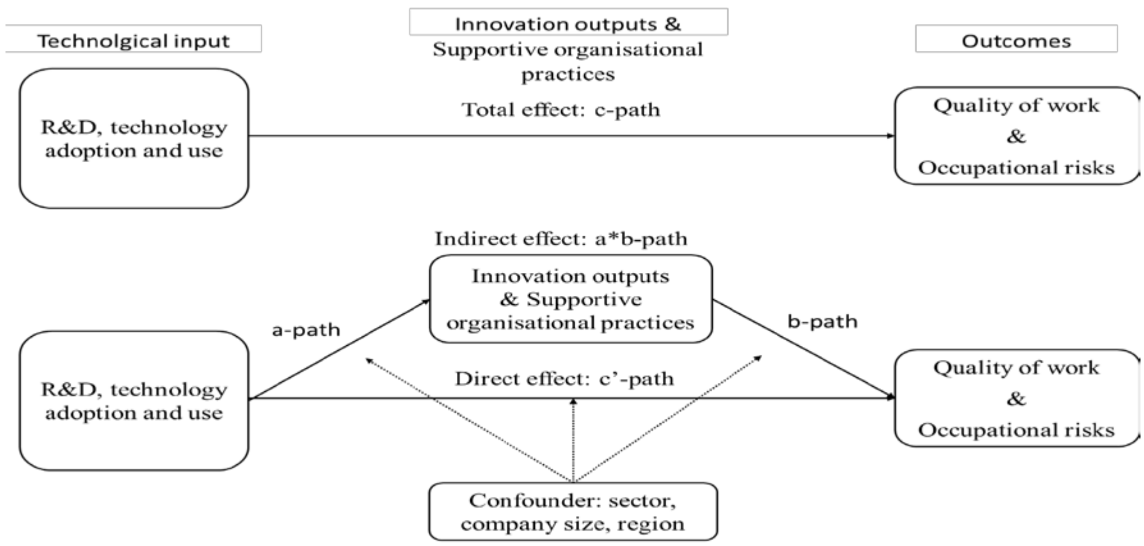
First, we calculated means (and SD) for all variables we used in the analyses: the technological inputs, innovation outputs, supportive organisational practices and outcomes, stratified by sector (services vs. production) and region (North-West vs South-East) (table 4).

Second, linear regression were used to analyse the relationship between the technological input variables and outcomes adjusted for sector, company size and region (table 5). Sector (production vs. services) and region (West and North vs South and East EU) were included in the model as dummy variables, and company size was added as the average size in a sector-country combination as well as the standard deviation of company size in that sector-country combination.

Third, to provide insight into the importance of differences across sectors and region, we stratified the analyses by sector and region (table 5).

Fourth, linear regression structural equation models (SEMs) were used to analyse the relationships between technological inputs and outcome variables and the mediating role of innovation outputs and supportive organisational practices. Figure 3 shows the mediation model. The total effects (c-paths) of the technological input variables on outcomes are shown in the upper part of the figure. The lower part of the figure shows the indirect effects of the output variables (a- and b-paths), as well as the direct effects of the technological input variables on the outcomes. It also shows that all analyses were adjusted for potential confounders including sector (production vs. services), average company size (and its SD), and region (West and Northern EU vs. South and East EU).

Figure 3. Visualisation of the multiple-mediation model.



In total 28 different SEM models were analysed; a different model for each technological input and outcome variable combination (four technological input variables x seven outcome variables). The number of observations for each model depended on the technological input variable and the dataset from which that variable was deducted:

- Design products & services from the ECS had 351 observations (28 countries and 15 sectors)
- In-house R&D from the CIS had 215 observations (28 countries and 14 sectors)
- Monitoring developments from the ECS had 351 observations (28 countries and 15 sectors)
- Digital technology adoption and use from the CICT had 259 observations (28 countries and 10 sectors)

The structural equation models were estimated in R statistical software using the lavaan package. The lavaan package is developed to perform latent variable analyses, such as structural equation models, in R statistical software. Mediation effects, such as the ones hypothesized in this study, can be estimated with this type of models. For each technological input and outcome combination, all output variables were added to the model as mediators. Accordingly, each model included multiple mediators, thus estimating the co-variance between them as well. For each mediator the indirect effect was estimated as well as the Ratio of the Indirect effect to the Total effect (RIT), where the total effect is the sum of all indirect effects. In case the indirect effect and direct effect have opposite signs, the absolute effects were used to compute the RIT. The RIT can be interpreted as the proportion mediated. We consider a p-value <0.05 to indicate a statistically significant mediation. As the statistical power is limited, we also indicate relationships with $0.05 \leq$ p-value < 0.10.

Fifth, we conducted additional SEM models for those technological input variables that had a negative association with outcome variables in a certain sector or region but no overall significant effect. We only did this for the negative relationships, as it is most interesting to understand the mechanisms behind the negative impact of the digital transformation for the development of policy options to mitigate these negative effects. In that case, we performed the SEM analyses for that specific sector or region, only. Based on the results, we did this for the relationship 1) between design products & services and low autonomy for the South and East EU, and 2) between monitoring external developments and psychological job demands for the South and East EU.

5 Results

Table 4 shows the mean (SD) of the technological input, innovation outputs, supportive organisational practices and outcomes for the total study population, and stratified by sector and region. R&D and technology adoption and use are similar in the services and production sector, although the Digital technology adoption and use indicator scores slightly higher in the services sector (0.56 vs. 0.51). In addition, this indicator is higher in the North-West region compared to South-East. Technological and non-technological innovation is also similar across industries and regions, with the exception of non-technological innovation only that is higher in the North-West compared to the South-East EU (0.16 vs 0.12). With regard to supportive organisational practices, we see that employee involvement and PSR risk management is higher in the services sectors as compared to the production sectors and in the North-West EU compared to the South-East EU. For the outcomes, we also see some differences between sectors and between regions. Emotional job demands and sitting is higher in the services sectors than in the production sectors, while lifting heavy loads, working tiring positions and environmental risks at the workplace are higher in the production sectors. Emotional job demands, low autonomy and tiring positions are higher in the South-East EU as compared to the North-West EU.

5.1 Relationship between technological inputs and outcomes

Table 5 shows the relationships between the technological input variables and occupational risks and quality of work for the total observations as well as for groups of sectors and regions. Overall, we observe that the R&D inputs were related to physical workload and occupational risks. For example, the design of products and services was related to lifting heavy loads with a beta of -0.92, which means that employees have to lift less in establishments where products and services are being developed. The relationships between R&D inputs and physical workload and occupational risks appear to be stronger in the services sectors as compared to the production sectors. The relationships between R&D investments and occupational risks were more pronounced in North-West EU than in the South-East, while there were fewer differences in physical workload between these regions. With regard to psychosocial risks, we see that the design of products and services at the establishment and monitoring external developments were related to more autonomy, especially in the services sectors and North-West EU. R&D investments were not related to emotional and psychological job demands, except for a relationship between design of products and services at the establishment and less emotional job demands in the production sectors.

We observe that Digital technology adoption and use is negatively related to low autonomy and positively with more sitting. There were no large differences across sectors and region, except for the relationship between digital technology and sitting, which appeared to be only present in the services sector. Digital technology was also positively related to less lifting heavy loads, working in tiring positions and workplace environmental risks, relationships that were present in both services and production sectors and regions.

Overall, it appears that relationships between technological inputs and outcomes differ inconsistently across sectors and regions. Sometimes the relationship with occupational risks and quality of work is more positive in one sector or region, while for other relationships the opposite is true. We have therefore controlled all further analyses for region, sector, and company size. Additionally, we performed subgroup analyses to gain more insight into reasons for associations that are in contrast with our hypotheses (see also chapter 4).

Table 4 Mean (SD) of the technological inputs, innovation outputs, mediators and outcomes for the total study population, and stratified by sector and region.

	Total population	Sector		Region	
		Services	Production	North-West	South-East
Technological inputs					
Design products & services	0.46 (0.23)	0.48 (0.22)	0.41 (0.24)	0.50 (0.22)	0.42 (0.22)
In-house R&D	0.43 (0.23)	0.41 (0.24)	0.45 (0.22)	0.49 (0.23)	0.38 (0.22)
Monitoring external developments	2.02 (0.29)	2.01 (0.26)	2.05 (0.34)	2.06 (0.27)*	1.98 (0.30)
Digital technology	0.55 (0.15)	0.56 (0.15)*	0.51 (0.12)	0.62 (0.13)*	0.49 (0.14)
Innovation outputs					
Technological and non-technological innovation	0.12 (0.10)	0.12 (0.10)	0.13 (0.12)	0.12 (0.10)	0.12 (0.11)
Non-technological innovation only	0.14 (0.10)	0.14 (0.10)	0.14 (0.11)	0.16 (0.10)*	0.12 (0.10)
Technological innovation only	0.39 (0.19)	0.40 (0.18)	0.36 (0.22)	0.39 (0.18)	0.39 (0.20)
Supportive organisational practices					
Autonomous teamwork	0.21 (0.16)	0.23 (0.16)*	0.18 (0.16)	0.27 (0.17)*	0.15 (0.13)
Formal employee representation	1.66 (0.56)	1.56 (0.53)*	1.85 (0.59)	1.83 (0.57)*	1.48 (0.51)
Discussion health & safety issues	1.27 (0.25)	1.33 (0.27)*	1.14 (0.15)	1.28 (0.24)	1.26 (0.26)
Employee involvement OSH measures	0.62 (0.20)	0.64 (0.19)	0.60 (0.22)	0.67 (0.18)*	0.57 (0.21)
OSH risk management	1.25 (0.69)	1.27 (0.67)	1.23 (0.74)	1.20 (0.66)	1.32 (0.72)
PSR risk management	1.13 (0.57)	1.07 (0.51)*	1.25 (0.67)	1.23 (0.52)*	1.02 (0.61)
Outcomes					
Emotional job demands	1.99 (0.76)	2.19 (0.73)*	1.57 (0.63)	1.86 (0.63)*	2.11 (0.85)
Psychological job demands	3.99 (1.26)	4.00 (1.23)	3.98 (1.33)	3.88 (1.09)	4.10 (1.42)
Low autonomy	1.03 (0.52)	1.02 (0.49)	1.06 (0.57)	0.84 (0.42)*	1.24 (0.53)
Lifting heavy loads	1.30 (0.94)	1.03 (0.77)*	1.83 (1.02)	1.36 (0.93)	1.24 (0.95)
Working in tiring positions	1.74 (0.87)	1.60 (0.77)*	2.02 (0.99)	1.51 (0.77)*	1.98 (0.90)
Repetitive work	0.24 (0.17)	0.25 (1.16)	0.23 (0.18)	0.23 (0.17)	0.25 (0.16)
Sitting	3.16 (1.26)	3.40 (1.33)*	2.66 (.096)	3.24 (1.23)	3.07 (1.29)
Workplace environmental risks	7.01 (5.03)	4.66 (2.84)*	11.66 (5.18)	6.56 (4.43)	7.48 (5.56)
Confounders					
Company size	55 (44)	48 (28)*	69 (64)	57 (35)*	53 (51)
Sector (%production)	34% (N=165)	0% (0)	100% (165)	34% (82)	34% (83)
Region (%North-West)	50% (N=243)	50% (161)	50% (82)	100% (243)	0% (0)

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
* Statistical significant differences between industries and regions ($p<0.05$).

Table 5. The relationships between technological inputs and employee level outcomes, for the total population and stratified by sector and region.

	Total population	Sector			Region
		Services	Production	North-west	South-East
	Beta (95%CI)	Beta (95%CI)	Beta (95%CI)	Beta (95%CI)	Beta (95%CI)
Design products & services					
Emotional job demands	-0.21(-0.54-0.12)	-0.04(-0.47-0.39)	-0.58(-1.1--0.07) **	-0.19(-0.57-0.19)	-0.23(-0.79-0.33)
Psychological job demands	0.27(-0.34-0.88)	0.29(-0.47-1.04)	0.28(-0.8-1.36)	-0.56(-1.28-0.15)	1.27(0.26-2.28) **
Low autonomy	-0.28(-0.51--0.04)**	-0.52(-0.8--0.25) **	0.26(-0.18-0.7)	-0.46(-0.73--0.19) **	-0.05(-0.45-0.35)
Lifting heavy loads	-0.92(-1.32--0.52)**	-1.31(-1.73--0.88)**	0.02(-0.83-0.87)	-0.88(-1.45--0.31)**	-0.91(-1.47--0.36)**
Tiring positions	-0.32(-0.7-0.07)	-0.29(-0.73-0.16)	-0.21(-0.99-0.57)	0.22(-0.39-0.82)	-0.75(-1.24--0.26)**
Repetitive work	0.04(-0.05-0.12)	-0.01(-0.11-0.09)	0.15(0.01-0.3) **	0(-0.11-0.11)	0.09(-0.03-0.21)
Sitting	1.07(0.5-1.64) **	1.29(0.52-2.06) **	0.31(-0.41-1.03)	0.83(0.08-1.58) **	1.28(0.4-2.15) **
Workplace environmental risks	-2.28(-4.01--0.55) **	-3.22(-4.86--1.58) **	0.84(-3.28-4.96)	-3.19(-5.38--1) **	-0.91(-3.64-1.81)
In-house R&D					
Emotional job demands	-0.16(-0.55-0.22)	-0.21(-0.68-0.27)	-0.11(-0.8-0.58)	-0.08(-0.57-0.41)	-0.25(-0.84-0.34)
Psychological job demands	0.41(-0.33-1.16)	0(-0.87-0.87)	1.21(-0.23-2.66)	0.28(-0.63-1.19)	0.58(-0.61-1.77)
Low autonomy	-0.28(-0.58-0.03)*	-0.38(-0.73--0.04) **	-0.05(-0.65-0.55)	-0.45(-0.83--0.07) **	-0.05(-0.54-0.41)
Lifting heavy loads	-1.14(-1.63--0.65)**	-1.54(-2.03--1.04)**	-0.19(-1.26-0.87)	-1.03(-1.75--0.3)**	-1.24(-1.92--0.56)**
Tiring positions	-0.43(-0.89-0.03)*	-0.49(-0.97--0.01)**	0.03(-0.95-1)	-0.31(-1.03-0.4)	-0.51(-1.1-0.07)*
Repetitive work	-0.12(-0.22--0.03) **	-0.25(-0.34--0.15) **	0.13(-0.07-0.34)	-0.13(-0.27-0.01)*	-0.11(-0.24-0.02)*
Sitting	1.69(1.01-2.27) **	2.39(1.68-3.1) **	0.17(-0.79-1.14)	1.43(0.63-2.22) **	1.92(0.63-2.22) **
Workplace environmental risks	-2.62(-4.91--0.33) **	-4.11(-6.23--2) **	1.96(-3.21-7.13)	-4.18(-7.14--1.22) **	-0.71(-4.2-2.78)
Monitoring external developments					
Emotional job demands	-0.04(-0.29-0.22)	-0.11(-0.48-0.26)	0.02(-0.32-0.37)	-0.22(-0.54-0.1)	0.08(-0.33-0.5)
Psychological job demands	0.31(-0.16-0.78)	0.07(-0.57-0.71)	0.65(-0.06-1.35)	-0.46(-1.05-0.14)	1.08(0.34-1.82) **
Low autonomy	-0.24(-0.42--0.06) **	-0.24(-0.49-0)*	-0.2(-0.49-0.09)	-0.25(-0.48--0.01) **	-0.22(-0.52-0.07)
Lifting heavy loads	-0.25(-0.56-0.07)	-0.47(-0.85--0.08)**	0.11(-0.45-0.67)	-0.28(-0.71-0.15)	-0.09(-0.56-0.39)
Tiring positions	0.04(-0.26-0.34)	-0.07(-0.45-0.3)	0.28(-0.23-0.79)	0.28(-0.16-0.73)	-0.11(-0.53-0.3)
Repetitive work	-0.07(-0.13-0) **	-0.05(-0.14-0.03)	-0.07(-0.17-0.02)	-0.09(-0.19-0) **	-0.01(-0.1-0.07)
Sitting	0.48(0.04-0.93) **	0.81(0.14-1.47) **	-0.04(-0.51-0.43)	0.31(-0.32-0.94)	0.47(-0.19-1.13)
Workplace environmental risks	-0.16(-1.51-1.19)	-1.3(-2.74-0.13)*	1.82(-0.87-4.5)	0.51(-1.35-2.38)	-0.15(-2.16-1.86)
Digital technology					
Emotional job demands	-0.13(-0.76-0.49)	-0.06(-0.78-0.65)	-0.04(-1.3-1.23)	-0.56(-1.21-0.09)*	0.39(-0.71-1.48)
Psychological job demands	0.23(-0.88-1.35)	0.15(-1.14-1.43)	0.71(-1.6-3.01)	0.03(-1.24-1.31)	0.46(-1.45-2.36)
Low autonomy	-1.25(-1.68--0.82) **	-1.29(-1.76--0.83) **	-1.38(-2.54--0.23) **	-1.09(-1.58--0.6) **	-1.43(-2.16--0.7) **
Lifting heavy loads	-1.47(-2.16--0.78)**	-1.28(-2.07--0.5)**	-2.28(-3.84--0.73)**	-1.14(-2.13--0.15)**	-1.81(-2.78--0.84)**
Tiring positions	-1.19(-1.88--0.51)**	-1.02(-1.77--0.27)**	-1.93(-3.73--0.13)**	-0.82(-1.93-0.29)	-1.56(-2.4--0.71)**
Repetitive work	-0.03(-0.18-0.13)	-0.08(-0.25-0.09)	0.22(-0.14-0.59)	-0.14(-0.35-0.06)	0.07(-0.15-0.29)
Sitting	2.48(1.34-3.63) **	2.68(1.29-4.07) **	0.93(-0.11-1.96)*	2.28(0.75-3.81) **	2.74(0.97-4.51) **
Workplace environmental risks	-6.49(-9.34--3.65) **	-5.52(-8.5--2.53) **	-9.81(-18.17--1.45) **	-8.12(-11.57--4.68) **	-4.76(-9.32--0.2) **

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)

Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.

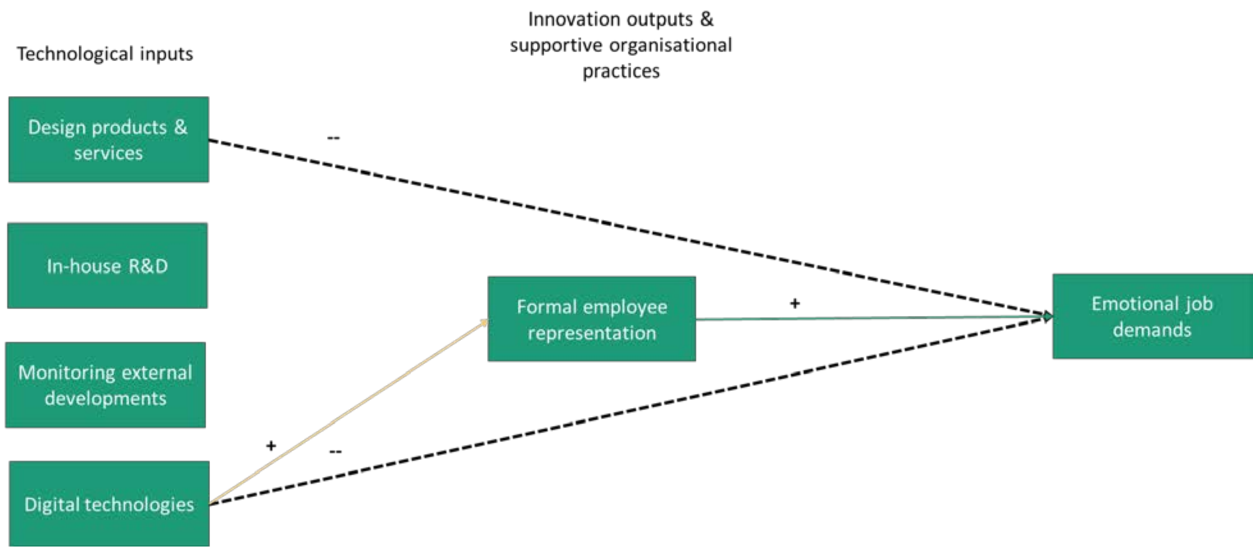
Boldface indicates statistical significance ($p<0.05$). *P<0.10, **P<0.05.

5.2 Results of the mediation analyses

Emotional job demands as outcome

Figure 4 presents the significant direct and indirect relationships between the technological inputs and emotional job demands. The effect size of the direct effects were much larger than that of the indirect effect. There were no significant total effects (c-path) (see appendix table A1). For in-house R&D and monitoring external developments, there were also no direct or indirect effects. We observed two direct effects: having more design products and services and more digital technology in establishments were directly (independent from innovation outputs and Supportive organisational practices) related to less emotional demands (beta: -0.40, 95%CI: -0.78 to -0.02, and beta: -0.82, 95%CI: -1.53 to -0.12, respectively) (see appendix table A1). Formal employee representation was a mediator in the relationship between the digital technology and emotional job demands: more technology was related with more formal employee representation, which was in turn related with more emotional job demands. There were no other mediators between any of the technological inputs and emotional job demands. Innovation outputs did not play a role in the relationship between technological inputs and emotional job demands.

Figure 4. Direct and indirect relationships via innovation outputs and supportive organisational practices between technological inputs and more emotional job demands.



Dotted lines indicate direct relationships; solid lines indicate indirect effects; plus sign indicates positive relationship; minus sign indicates negative relationship; effect sizes of direct effects are larger than indirect effects, which is indicated by a double sign.

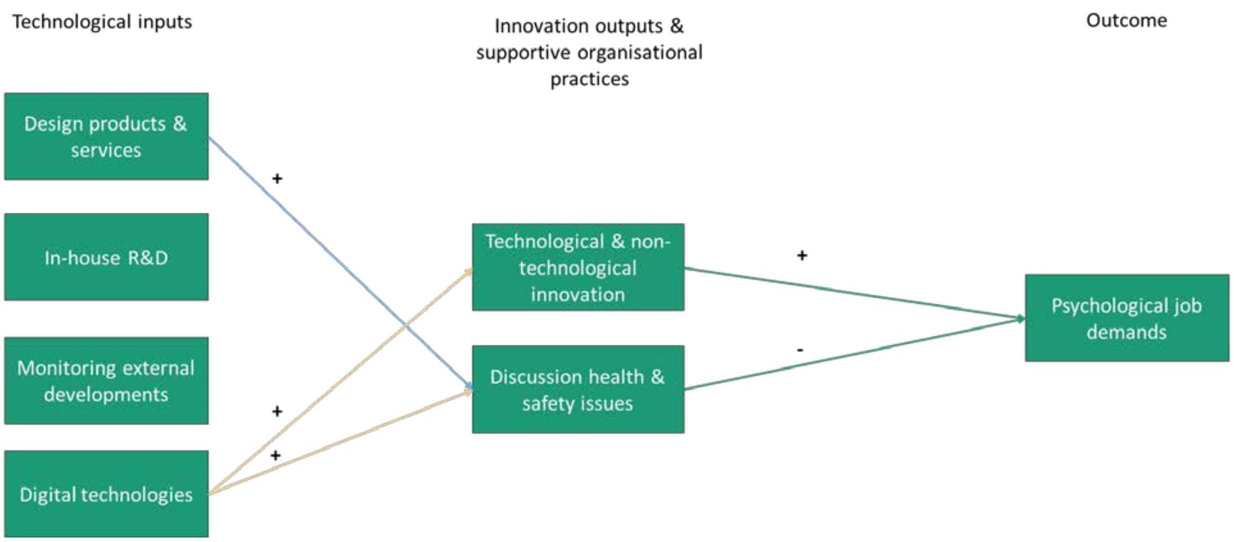
Psychological job demands as outcome

Figure 5 presents the significant indirect relationships between the technological inputs and psychological job demands. There were no significant total (c-path) or direct (c'-paths) effects (see appendix table A2). We found that the combination of technological and non-technological innovation played a significant mediating role in the relationship between digital technology and psychological job demands. More digital technology was related to more innovation, which was in turn related to more psychological job demands.

We observed two indirect effects via the mediator discussion of health & safety issues. More design of products and services at the establishment and more digital technology were related with more discussion on health & safety issues, which in turn was related with less psychological job demands. Innovation outputs did not play a role in the relationship between technological input and psychological job demands.

As shown in table 5, design products & services and monitoring external developments were related to more psychological job demands in the South-East EU only. Therefore, in an additional subgroup analyses, we modelled the SEM model for the South-East region only. In the relationship between the design products and services and psychological job demands, we found no significant direct effect, but we found that PSR management was a mediator (appendix table A3). More design & products at the establishment was related to better PSR risk management, which was related to more psychological job demands.

Figure 5. Direct and indirect relationships via innovation outputs and supportive organisational practices between technological inputs and more psychological job demands.

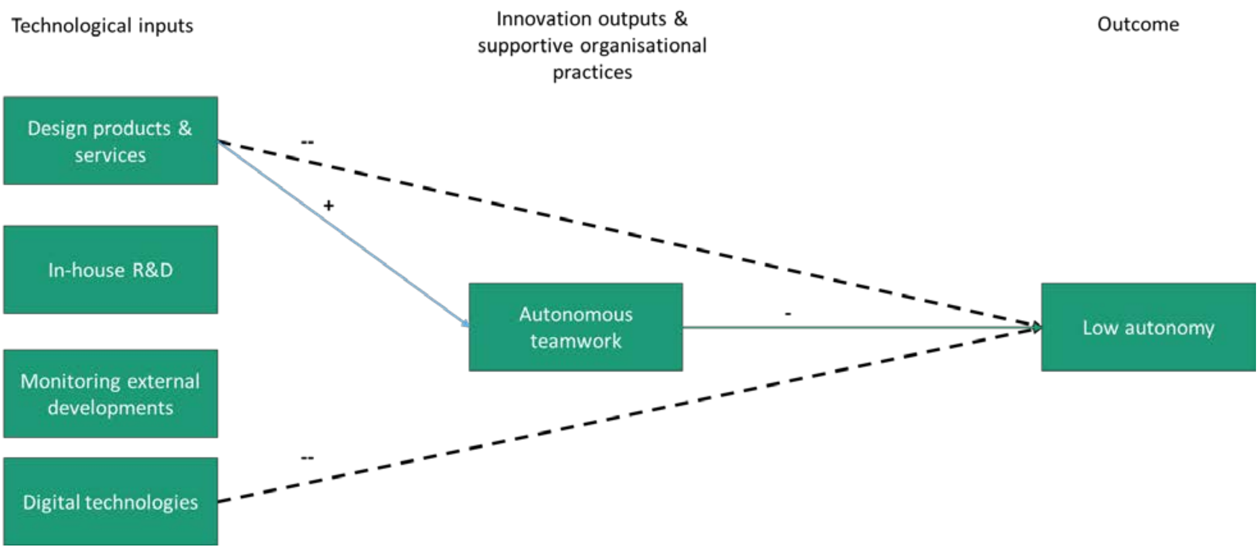


Solid lines indicate indirect effects; plus sign indicates positive relationship; minus sign indicates negative relationship.

Low autonomy as outcome

Figure 6 presents the significant direct and indirect relationships between the technological inputs and low autonomy. The effect size of the direct effects were much larger than that of the indirect effect. There were significant total effects (c-paths) for development of products and services at the establishment and digital technology (See appendix table A4). For these two technological input variables, we also observed direct effects (c'-paths). Analyses showed that more design of products and services development (beta: -0.31, 95%CI: -0.57--0.04) and more digital technology (beta: -1.21, 95%CI: -1.71--0.72) were directly related to more autonomy. Autonomous teamwork was the only significant mediator: more design products and services development was related to more self-managing teams, which was related to more autonomy. Innovation outputs did not play a role in the relationship between technological input and autonomy.

Figure 6. Direct and indirect relationships via innovation outputs and supportive organisational practices between technological inputs and more low autonomy

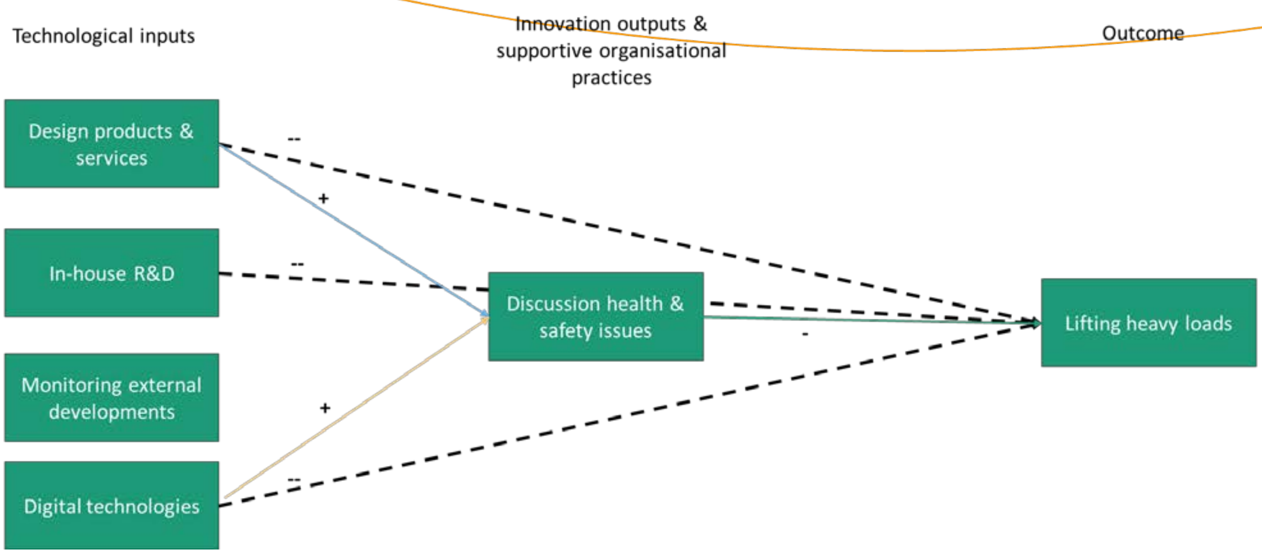


Dotted lines indicate direct relationships; solid lines indicate indirect effects; plus sign indicates positive relationship; minus sign indicates negative relationship; effect sizes of direct effects are larger than indirect effects, which is indicated by a double sign.

Lifting heavy loads as outcome

Figure 7 presents the significant direct and indirect relationships between the technological inputs and lifting heavy loads. The effect size of the direct effects were much larger than that of the indirect effect. There were three significant total (c-path) and direct (c'-path) effects (See appendix table A5). More design of products and services development, more in-house R&D, and more digital technology were directly (independent from innovation outputs and Supportive organisational practices) related to less lifting of heavy loads. More design of products and services at the establishment and more digital technology were related to more discussion on health & safety issues, which in turn was related to less lifting heavy loads. None of the innovation outputs mediated the relationship between the technological input variables and lifting heavy loads.

Figure 7. Direct and indirect relationships via innovation outputs and supportive organisational practices between technological inputs and more lifting heavy loads.



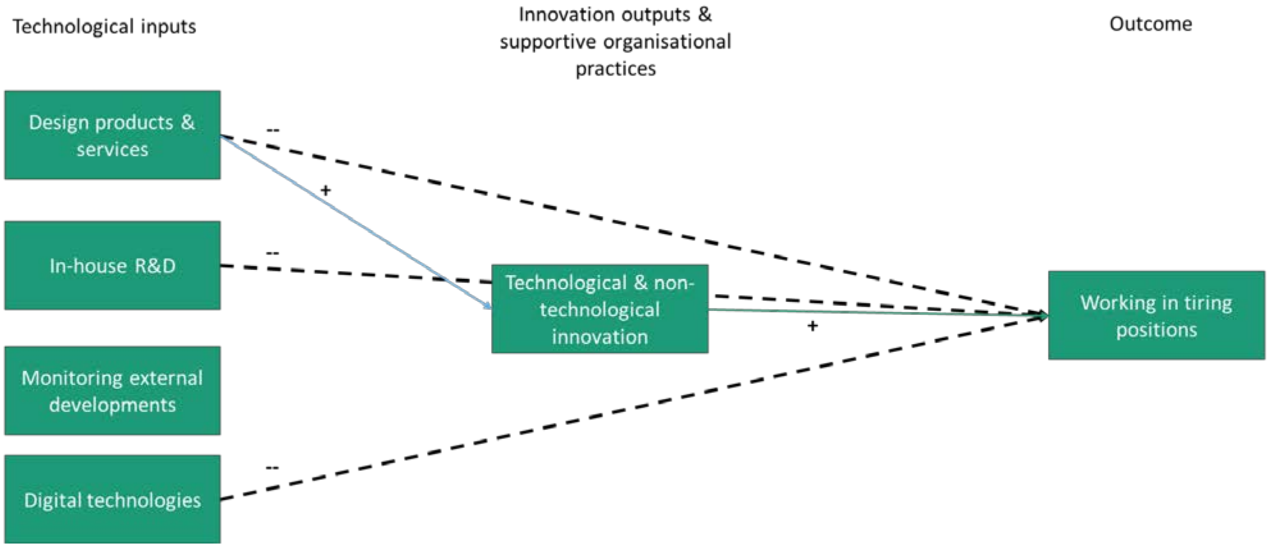
Dotted lines indicate direct relationships; solid lines indicate indirect effects; plus sign indicates positive relationship; minus sign indicates negative relationship; effect sizes of direct effects are larger than indirect effects, which is indicated by a double sign.

Working in tiring positions as outcome

Figure 8 presents the significant direct and indirect relationships between the technological inputs and working in tiring positions. The effect size of the direct effects were much larger than that of the indirect effect. Similar as for lifting heavy loads, we found three significant total (c-path) and direct (c'-path) effects of technological inputs to working in tiring positions (See appendix table A6). More design of products and services development, more in-house R&D, and more digital technology were directly (independent from innovation outputs and Supportive organisational practices) related to less working in tiring positions. None of the Supportive organisational practices mediated the relationship between the technological input variables and working in tiring positions.

However, we did find that the combination of technological and non-technological innovation played a significant mediating role in the relationship between the design of products and services development and working in tiring positions. More design of products and services development was related to more innovation, which was in turn related to more working in tiring positions. To get insight into why we found this relationship, we performed subgroup analyses. We found that the relationship between the combination of technological and non-technological innovation and working in tiring positions was present in the production as well as in the services sectors, but we only observed this relationship in the East EU, and not in the South, North or West.

Figure 8. Direct and indirect relationships via innovation outputs and supportive organisational practices between technological inputs and more working in tiring positions.



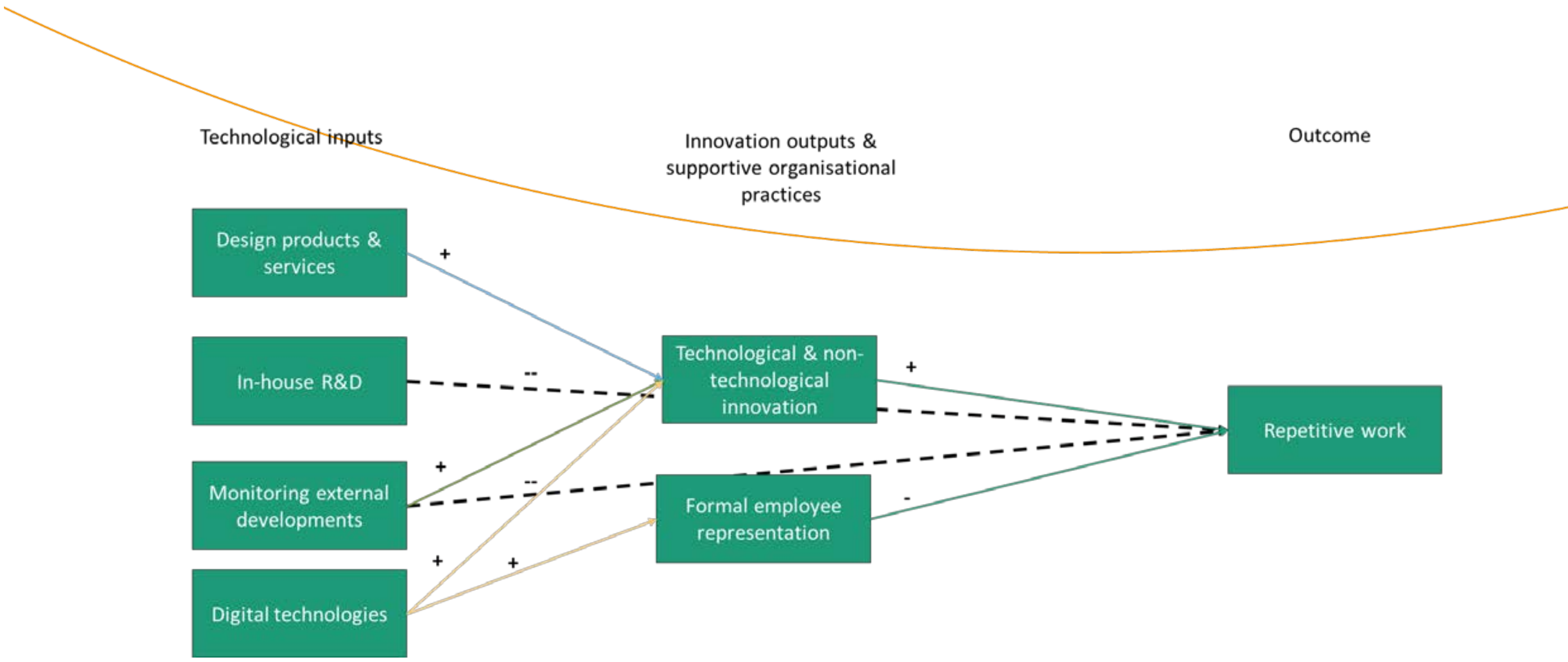
Dotted lines indicate direct relationships; solid lines indicate indirect effects; plus sign indicates positive relationship; minus sign indicates negative relationship; effect sizes of direct effects are larger than indirect effects, which is indicated by a double sign.

Repetitive work as outcome

Figure 9 presents the significant direct and indirect relationships between the technological inputs and repetitive work. The effect size of the direct effects were much larger than that of the indirect effects. We observed total (c-path) and direct (c'-path) effects of the relationship of more in-house R&D expenditure and more monitoring of external developments with less repetitive work (See appendix table A7). We found that the combination of technological and non-technological innovation played a significant mediating role for three technological input variables. More design of product and services development, more monitoring of external developments, and more digital technology was related to more innovation, which in turn was related with more repetitive work. digital technology was also related to more formal employee representation, which in turn was related to less repetitive work.

As shown in table 5, more design of products & services was related to more repetitive work in the production sectors, but not in the services sectors. Therefore, we estimated, in an additional subgroup analysis, the SEM model for this relationship in the production sector only (appendix table A8). We observed that, in contrast to the analysis including both sectors, more design of products & services development in the production sector was directly related to more repetitive work, and that there were no significant mediators. The indirect effect of innovation (beta = 0.05, 95%CI: -0.02 to 0.11), however, was the same in the production sectors as for both industries combined, but statistically not significant in the production sectors due to less statistical power.

Figure 9. Direct and indirect relationships via innovation outputs and supportive organisational practices between technological inputs and more repetitive work.



Dotted line indicate direct relationships; soled lines indicate indirect effects; plus sign indicates positive relationship; minus sign indicates negative relationship; effect sizes of direct effects are larger than indirect effects, which is indicated by a double sign.

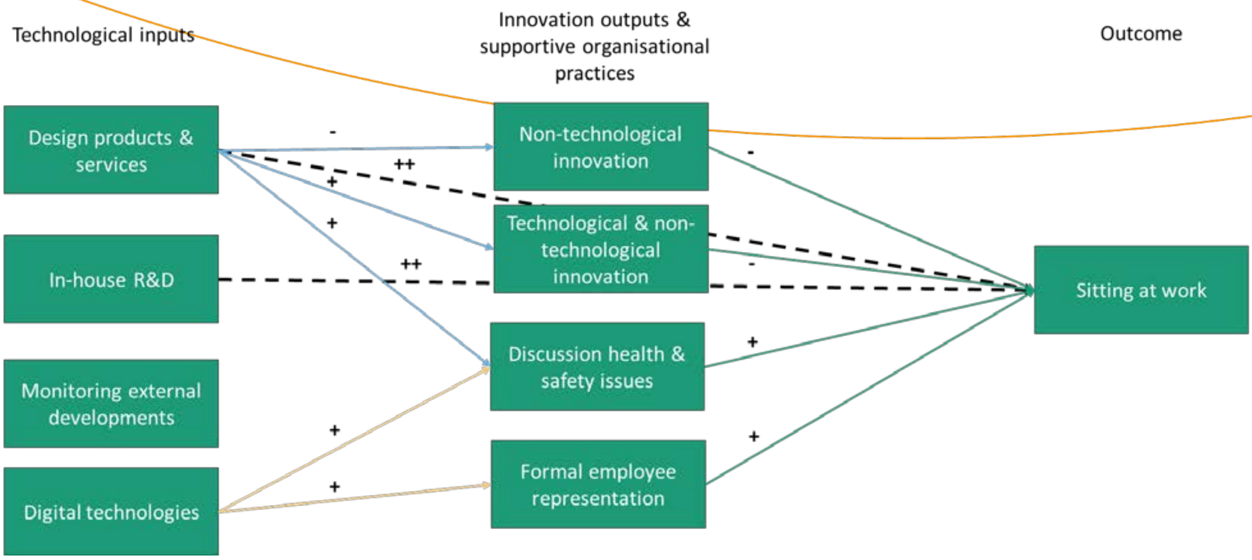
Sitting as outcome

Figure 10 presents the significant direct and indirect relationships between the technological inputs and sitting. The effect size of the direct effects were much larger than that of the indirect effect. There were three significant total effects (c-path): more design of products & services, more in-house R&D and more digital technology were related to more sitting at work (See appendix table A9). We observed two direct effects (c'-path): more design of products & services and more digital technology were directly (independent from innovation outputs and supportive organisational practices) related to more sitting at work (beta: 1.08, 95%CI: 0.48 to 1.69, and beta: 1.66, 95%CI: 1.14 to 2.17, respectively).

Non-technological innovation only mediated the relationship in such a way that more design of products & services relates to less sitting at work, because more design of products and services leads to less exclusive non-technical innovations, which relates to less sitting at work. At the same time, more design of products & services, relates to more non-technological innovation that coincide with technological innovations, and this combination of innovations also leads to less sitting. In subgroup analyses, we observed that the relationship between innovation and less sitting at work was present in the services sectors, and not in the production sectors. This relationship was strongest in West EU, but also present in South and East EU; not in the North EU.

Discussion of health & safety issues and formal employee representation were mediators in the relationship between the digital technology and sitting at work: more digital technology was related with more discussion of health & safety issues and formal employee representation, which was in turn related with more sitting at work.

Figure 10. Direct and indirect relationships via innovation outputs and supportive organisational practices between technological inputs and more sitting



Dotted lines indicate direct relationships; solid lines indicate indirect effects; plus sign indicates positive relationship; minus sign indicates negative relationship; effect sizes of direct effects are larger than indirect effects, which is indicated by a double sign.

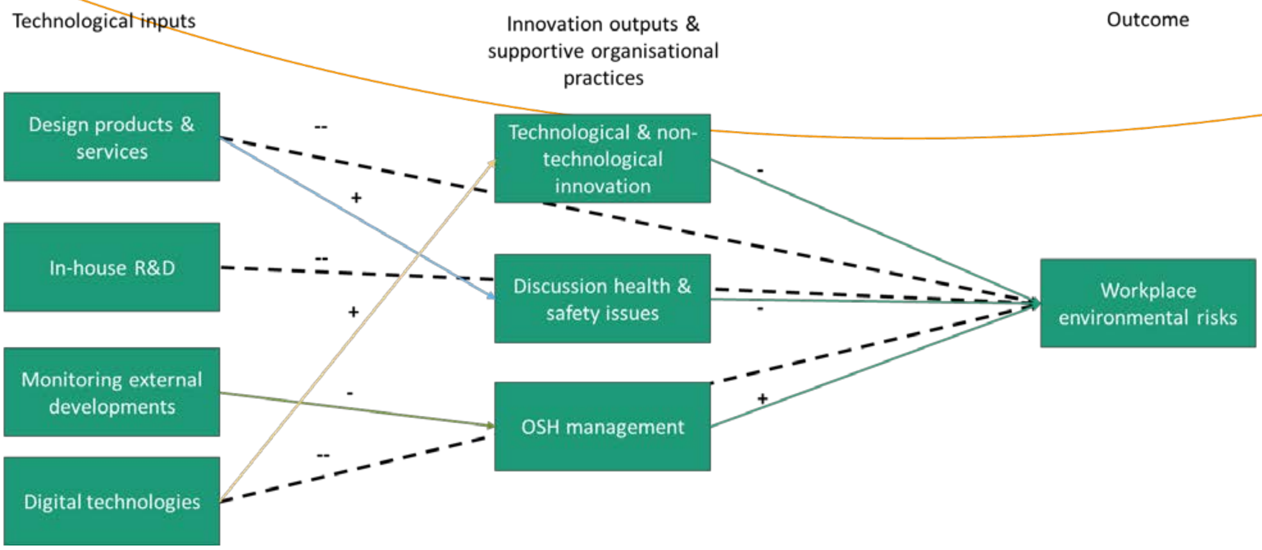
Environmental risks at the workplace as outcome

Figure 11 presents the significant direct and indirect relationships between the technological inputs and risk in the workplace environment. The effect size of the direct effects were much larger than that of the indirect effect. We observed significant total (c-path) and direct (c'-path) effects of the relationship of more design of products and services, more in-house R&D expenditure and more monitoring of external developments with less workplace environmental risks (appendix table A10). The direct effects were beta = -3.05 (95%CI: -4.96 to -1.14), beta = -2.32 (95%CI: -4.56 to -0.08), and beta = -5.72 (95%CI: -8.91 to -2.53), respectively.

The combination of technological and non-technological innovation was a significant mediator in the relationship between Digital technology and environmental risks: more Digital technology was related to more innovation, which in turn was related with less environmental risks.

Discussion of health & safety issues with staff and teams was a mediator: more design of products and services at the establishment was related to more discussion, which in turn was related to less environmental risks. OSH risk management (i.e. having sufficient time, budget, and expertise for implementing OSH measures) was also a mediator: more monitoring of external developments was related with less OSH management, which in turn was related with more environmental risks.

Figure 11. Direct and indirect relationships via innovation outputs and supportive organisational practices between technological inputs and more environmental risks.



Dotted line indicate direct relationships; soled lines indicate indirect effects; plus sign indicates positive relationship; minus sign indicates negative relationship; effect sizes of direct effects are larger than indirect effects, which is indicated by a double sign.

6 Summary of results

Overall, technological inputs were related to less occupational risks and a better quality of work (Table 6). Design of products and services at the establishment and Digital technology were both related to less psychosocial risks (less emotional demands and more autonomy), less lifting heavy loads, less working in tiring positions and less environmental risks at the workplace. In-house R&D expenditure was related to less physical workload and less environmental risks, but not to psychosocial risks. The only overall negative effect of technological inputs was found for sitting at work: more design of products & services, more in-house R&D expenditure, and more Digital technology were related to more sitting at work.

In addition, 'Monitoring external developments' was only related to repetitive work and not to any other occupational risk analysed here. This finding suggests that several indicators of technological developments are found to be related to quality of work and occupational risks, but not all.

Table 6. Summary of the relationships between technological inputs and occupational risks and quality of work (green = positive relationship (/less demands); red = negative relationship (/more demands).

	Design products & services	In-house R&D	Monitoring external developments	Digital technology
Emotional job demands	x			x
Autonomy	x			x
Lifting heavy loads	x	x		x
Working in tiring positions	x	x		x
Repetitive work		x	x	
Sitting at work	x	x		x
Workplace environmental risks	x	x		x

*Technological inputs were not directly related to psychological job demands.

Table 7. shows which factors significantly mediated relationships between the technological inputs and outcomes. It should be noted that the effect sizes of the indirect effects were much smaller than the direct effects, which means that the supportive organizational practices only explain a relatively small part of the relationships between technological inputs and occupational risks and quality of work. Innovation outputs mediated relationships between technology and physical risks as well as environmental risks at the workplace. This was the case for organisations with 'complex' innovation: organisations that implemented both technological and non-technological innovations. These types of innovations were related to less sitting at work and less environmental risks, but were related to a higher exposure to more working in tiring positions, more repetitive work and more psychological job demands.

The presence of autonomous teamwork mediated the relationship between technological inputs and more autonomy. More discussion on health & safety issues mediated the relationship between technological inputs and less psychological job demands, less lifting heavy loads and less environmental risks. Contrary to expectations, formal employee representation was related to more emotional job demands and more sitting at work.

Table 7. Significant innovation outputs and Supportive organisational practices in the relationship between technological inputs and occupational risks and quality of work.

	Positive	Negative
Innovation outputs		
Technological & non-technological innovations	Sitting at work Workplace environmental risks	Tiring positions Repetitive work Psychological job demands
Non-technological innovations only	--	Sitting at work
Technological innovations only	--	--
Supportive organisational practices		
Autonomous teamwork	Autonomy	--
Formal employee representation		Emotional job demands Sitting at work
Discussion health & safety issues	Repetitive work Psychological job demands Workplace environmental risks Lifting heavy loads	Sitting at work
OSH risk management	Workplace environmental risks	--

7 Discussion

Interpretation of our findings is not straightforward due to the use of aggregated data between 2010-2015. The substitution of individual (micro-)data with aggregated (macro-)data leads to loss of variation within subgroups. It makes it particularly difficult to explain findings that are in contrast to expectations and that are only present in certain subgroups. The results imply that 1) overall the **investments in technological inputs have a favourable relationship with quality of work and occupational risks for the EU as a whole, and 2) this is partly explained by the fact that some organisations combine technology implementation with certain actions that make OSH risks manageable**. **Examples are employee involvement, discussing OSH in the workplace, employee representations, and organisational innovation. These are factors related to high-road companies where employees are provided with the opportunity to cope well with technological changes and work demands thanks to a supportive environment.** Previous studies showed that when companies focus on employee involvement they are more likely to have a constructive work environment, supportive leadership style, constructive employment relationships (Bailey et al., 2017). **Employee involvement is also associated with better innovation adoption** (Rangus & Slavec, 2017), **which makes it more likely that technology is more aligned with the needs of employees, resulting in fewer OSH risks.** In the next paragraphs, we discuss this in more detail for psychosocial risks, physical workload and workplace environmental risks, separately.

In addition, the mediating impact of the formal employee representation acted different as a mediator as compared to more informal employee activities like employee involvement and discussions on work and health issues between management, staff and employees. The formal employee representation is a formalisation of the employees' voice having a more political role in bargaining and setting aims for employee benefits. As opposed to the other supportive organisational activities, the formal employee representation is often only present in the larger organisations (in practice often in 50 plus sized organisations). These characteristics of formal employee representation may partly have explained (or blurred) its mediating role.

Psychosocial risks

In contrast to our hypothesis, we observed that design of products and services at the establishment and digital technology adoption and use were related to less psychosocial risks in term of less emotional demands and more autonomy. With regard to psychological demands, it has been argued that technology may increase the pace of work and lead to information overload (Marsh et al., 2022). However, new technologies may also offer organisations opportunities to better manage the workload, such as tools to work at other places than the office, or job crafting tools that give the opportunity to redesign work more in line with the needs of employees (Bakker & Demerouti, 2014). This is in line with our finding of digital technology being related with more autonomy. Although studies found that technology could be used to monitor tasks and take over meaningful decision making about work (Das et al., 2020; Stefano, 2019), technology may also be used to increase autonomy. Parker and Grote (2020) and Demerouti (2020) state that there are positive and negative design possibilities that affect the degree of autonomy and control over one's own work, task variation, feedback, social aspects and task demands. Thus, our findings may imply that organisations most often use or implement technologies in such a way that it increases autonomy.

The relationship between technology and psychological job demands in the present study was quite weak, and technological inputs were only related to more psychological demands in the South-East EU. **We also found that technological inputs were related to less psychological demands via a form of employee involvement.** This is a new result and largely in contrast to previous findings that indicate that computer work is related to intensification of work, which was in our study not the case in the North-West EU (March et al., 2022; Yin et al., 2018). Our findings implicate that organisations that introduce new products, services or digital technology may reduce psychological job demands in cases where there is discussion between staff and teams about health & safety issues. Although we expected other forms of employee involvement to be of importance as well, this is in line with literature of workplace innovation and psychosocial risk management, which suggest that employee participation in the introduction of new technologies is essential for employee health and successful implementation of innovations (Demerouti, 2020; Nielsen & Randall, 2013; Oeij et al, 2017; Oeij et al, 2019; Parker et al., 2020; Westgaard & Winkel, 2011).

We know little about the relationship between technological inputs and emotional job demands. Several potential reasons may explain our findings of technology being related with less emotional job demands. The use of digital technology may reduce the time that employees are in direct contact with clients, costumers and patients, resulting in reducing the chance of encountering emotionally disturbing situations. Windeler et al. (2017) also found that high demands to socially interact with other people in work decreased after the introduction of (part-time) telework practices, which may also lower the amount of time spent in emotionally disturbing situations.

One important issue may that makes understanding the results on emotional job demands difficult is the fact that due to the necessity to combine the data sets, many or maybe even most enterprises from the typical public services like health care, enforcement services like the police and schools were lost in the data set. This means that some specific aspects of 'emotional job demands' were lost. It is not very clear how this may have affected the results.

Physical working conditions

R&D investments and digital technology adoption were related to less physical workload in terms of less lifting, tiring positions and repetitive work. In line with our results, automatisation has been related to less lifting and tiring positions (Stacey et al., 2018). Findings with regard to repetitive work have been more inconsistent: the EU OSHA study (Stacey et al., 2018) found digital technology to be related to an increase of repetitive work, while Krause and Douwes (2019) found in a qualitative study that digitalisation of working conditions was sometimes related to less repetitive work (e.g. picking robots in horticulture) and sometimes to more repetitive work (e.g. input and output tasks remained manual tasks). Our findings also indicate that the effect of technological inputs, and in particular the effect of R&D investments differs per context: design of products & services at the establishment was related to more repetitive work in production sector but not in the services sector, while in-house R&D expenditure was related to less repetitive work in the services sector and not in the production sector. A potential explanation of more repetitive work in the production sectors is that automatisation and standardisation of production processes is used to increase productivity and reduce costs, which may be detrimental for the quality of remaining manual work, resulting in an increase in repetitive work. Digital technologies may take over tasks of employees, reducing the variety of tasks they need to perform resulting in an increase of the amount of repetitive work. Thus, overall, technological inputs relate to less physical workload in this study, but contrasting findings are found in certain contexts.

In the present study, **supportive organisational practices positively mediated the relationships between technological inputs, and lifting heavy loads and repetitive work.** For repetitive work, we observed a significant role of formal employee representation, implying that this kind of employee representation was related to more repetitive work when technologies are present or are implemented. This may be an example of the 'blurring' effect of the more political role of the formal employee representation mentioned earlier in this discussion. Another reason might be that within their role as the 'employee voice', the formal employee representation may have bargained for a better 'quality of work; like reduced physical workload. This may have resulted in more sitting. Whereas the results indeed did show that the discussion on health & safety issues between staff and teams was of importance for reduction of lifting heavy loads when investing in new knowledge and using of digital technologies. **The combination of technological and non-technological innovations mediated the relationships between technological inputs and working tiring positions and repetitive work.** As mentioned above, the introduction of new technologies may for some occupations increase repetitive work as automatisation takes over certain tasks, increasing the amount of repetitive tasks. In addition, automatisation may lead to increased production rate, increasing the workload of remaining manual, repetitive tasks. The relationship between innovation and working in tiring positions was somewhat unexpected. It might be explained by complex innovations that do not rely on digital technologies in, for example, infrastructure or maintenance. Sensitivity analysis also indicated that this relationship was only present in the East EU and not in other regions. It might be that East EU organisations implement other types of technologies in different ways compared to the rest of the EU, which may increase working in tiring positions. Organisations in especially West- and North EU have more attention for mitigating physical workload at the workplace when introducing new technologies due to more developed employment relationships and working condition policies and regulations.

In our study, technological inputs were related to more sedentary work (sitting) in the services sectors, but not in the production sectors. This can be explained by the increased use of digital, online work, and possibilities of technology to control, monitor and maintain work processes remotely (Stacey et al., 2018). The role of the innovation outputs and supportive organisational practices in the relationship between R&D investments and digital technology adoption and use and sitting is difficult to explain. It seems that employee involvement does not have a positive effect on less sitting at work, and both formal employee representation and more discussion of health & safety issues were even related to more sitting at work. In the previous paragraph, we provided some explanation on these findings.

Innovation seems to have a favourable influence on the relationship between design of products and services at the establishment and less sitting at work in the services sector only. This might be due to non-digital innovations in, for example, services sectors like the hotels and restaurants, food delivery or retail, and in occupations where employees stand or walk a lot. We saw this for non-technological innovations either with or without a technological innovation, indicating that organisational changes that are implemented together with the development of new knowledge have a positive influence on less sitting at work in the services sector.

Environmental risks at the workplace

We observed a positive relationship between organisations that are actively investing in R&D and lower environmental risks at the workplace, mainly in the services sectors and North-West EU. This seems intuitively correct as we may assume that organisations that innovate work with relatively modern machinery, which tend to be safer. It may be that innovation-driven companies are rejecting traditional working methods, such as assembly lines. This takes humans away from the 'sharp end' of work and creates a distance between the hazard and the person resulting in safer work.

As expected, we observed that the **relationship between design of products and services and less environmental risks was mediated by discussion of health & safety issues between management and teams.** These results imply that it is important to involve employees when developing and introducing new technologies to mitigate environmental and safety risks at work. We also observed that **digital technology was, in all sectors and regions, related to more technological and non-technological innovation, which in turn was related to less environmental risks**. This implies that innovations related to digital may also mitigate environmental risks, possibly because employees are less in contact with machinery that cause, for example, noise and safety risks at work (Busick, 2016; Katwala, 2017).

Strengths & limitation

We have used unique combinations of datasets at the EU-wide level to provide evidence about the relations of technological transformation on quality of work and occupational risks. These datasets allowed us to develop an enriched measurement frame of the ongoing technological transformation with three novelties: first, a composite indicator of digital technology adoption and use that takes into account the diversity of ICTs and digital technologies; second, combined measures of technological and non-technological innovations; third, we considered autonomous teamwork, employee representation and management of OSH risks as mediators in the relationship between technological transformation and quality of work and occupational risks.

Data access and harmonisation issues have raised a number of problems as this was complex, particularly because there is no option to link the data at the individual worker or company level. Had this been possible, the number of observations could have increased, and with it the variance, resulting in a further increase in the validity of the analyses. Second, we integrated the datasets based on the “common cell” constructed from the key variables country and sector, and intended to use company size as a third variable to combine datasets and increase statistical power. Company size could, however, not be used robustly because this variable was not harmonised between surveys. We were able to adjust the analyses for company size, sector and region, increasing the robustness of our findings. Third, as the most recent EU-wide data on employee level outcomes was 2015, we were not able to investigate new and advanced technologies, nor can we say anything about the impact of more recent developments like COVID-19. Fourth, while the data were taken from different surveys that were collected in consecutive years, we analysed correlations and associations between variables, but it was not possible to indicate any causal direction in these relationships. Fifth, the observed relationships apply to the whole dataset, certain region or sector, but they might be differently based on a specific context of an enterprise or of a technological development (input). Despite these limitations, using different sources in an integrated way gave us the opportunity to examine simultaneously the behaviour of organisations in terms of technological investments, work and organisational practices, innovation, and their impacts on quality of work and occupational risks.

8 Conclusion and recommendations

Our results imply that (digital) technology has more favourable than unfavourable effects regarding better quality of work and less occupational risks. We observed that (digital) technology was directly related to less emotional job demands, more autonomy, less lifting heavy loads, less working in tiring positions, less repetitive work and less workplace environmental risks, but with more sitting at work. This is especially the case for the service sectors and the North-West EU. Digital technology was not related to psychological job demands.

Innovation and employee involvement played a mediating role for physical workload and environmental risks at the workplace. These indirect effects were, however, smaller in effect size than the direct effects, explaining only part of the relations between digital technology and physical workload and environmental risks. The introduction of technological and non-technological innovations was, in particular in the service sectors, associated with more physical workload and less workplace environmental risks. This implies that pro-active policies at the company level are needed to mitigate the effect of such innovations on physical workload. This begins with the selection of new technologies that have beneficial effects on all aspects of job quality but also by the way technologies are developed and implemented and how work is organized.

The impact of investments in new knowledge and use of digital technologies on psychosocial risks was mediated by some forms of employee involvement. In particular, we found that having autonomous teamwork, formal employee representation and discussions on health & safety issues with teams to have a beneficial effect on less psychosocial risks and less workplace environmental risks. These findings highlight the importance of human-centered design principles and a high-road company strategy, such as workplace innovation and psychosocial risk management, in organisations that work with or introduce new technologies. Workplace innovation practices or interventions help to improve both organisational performance and the quality of jobs at the same time by involving and empowering employees. This helps to adapt to changes and challenges of new (digital) technologies (e.g. Oeij et al, 2017; Oeij et al, 2019). Workplace innovation practices can be strengthened by integrating psychosocial and OSH risk management strategies that also strive to involve employees by proper communication and by including them in decision making when (technological) changes occur (Dollard , 2007; Dollard & Bakker, 2010; Dollard et al, 2012; Nielsen & Noblet 2018), and by designing the work with technology that supports people's work, increase autonomy and job resources (Demerouti, 2020). Our findings imply that integrating such supportive organisational practices with investments in new knowledge and digital technologies may contribute better quality of work and less occupational risks.

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10 Appendix

Table A1. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and emotional job demands.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	-0.27 (-0.60-0.06)	**-0.39 (-0.77--0.01)****				
Discussion health & safety issues			**0.18 (0.07-0.29)****	**0.35 (0.03-0.67)****	0.06 (-0.01-0.13)*	0.11
In-house R&D	-0.14 (-0.52-0.24)	-0.12 (-0.51-0.27)				
No mediators			NA	NA	NA	NA
Monitoring technological developments	-0.11 (-0.37-0.15)	-0.16 (-0.43-0.10)				
No mediators			NA	NA	NA	NA
Digital technology	-0.13 (-0.74-0.48)	**-0.78 (-1.47--0.08)****				
Discussion health & safety issues			**0.57 (0.35-0.79)****	0.35 (0.01-0.72)*	0.20 (-0.02-0.42)*	0.12
Formal employee representation			**1.13 (0.74-1.51)****	**0.31 (0.11-0.50)****	**0.35 (0.10-0.60)****	0.20

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.

Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance ($p<0.05$). Only outputs and mediators with $P<0.10$ are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more emotional job demands.

Table A2. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and psychological job demands.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	0.22 (-0.4-0.85)	0.05 (-0.62-0.75)				
Discussion health & safety issues			0.18 (0.07-0.29)**	-0.81 (-1.37--0.25)**	-0.15 (-0.28--0.01)**	0.18
PSR risk management			0.22 (-0.02-0.46)*	0.68 (0.42-0.93)**	0.15 (-0.03-0.32)*	0.18
In-house R&D	0.36 (-0.39-1.11)	0.40 (-0.29-1.10)				
No mediators			NA	NA	NA	NA
Monitoring technological developments	0.19 (-0.30-0.67)	0.03 (-0.44-0.05)				
PSR risk management			0.17 (-0.02-0.36)*	0.68 (0.42-0.93)**	0.12 (-0.02-0.25)*	0.30
Digital technology	0.23 (-0.86-1.33)	-0.11 (-1.29-1.06)				
Technological and non-technological innovation			0.39 (0.26-0.53)**	1.50 (0.49-2.50)**	0.59 (0.14-1.03)**	0.31
Discussion health & safety issues			0.57 (0.35-0.79)**	-1.21 (-1.83--0.59)**	-0.69 (-1.13--0.25)**	0.37

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance ($p<0.05$). Only outputs and mediators with $P<0.10$ are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more psychological job demands.

Table A3. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and psychological job demands for South-East EU.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)
Design products & services	**1.17 (0.13-2.21)****	0.54 (-0.53-1.61)			
OSH risk management			**0.54 (0.15-0.93)****	**0.68 (0.3-1.05)****	**0.37 (0.03-0.7)****
Monitoring technological developments	**1.03 (0.26-1.81)****	0.68 (-0.04-1.4)*			
Technological and non-technological innovation			**0.14 (0.04-0.24)****	**1.41 (0.19-2.63)****	0.19 (-0.02-0.41)*

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance (p<0.05). Only outputs and mediators with P<0.10 are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more psychological job demands.

Table A4. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and low autonomy.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	**-0.31 (-0.55--0.07)****	**-0.29 (-0.56--0.03)****				
Autonomous teamwork			**0.12 (0.05-0.20)****	**-0.58 (-0.93--0.22)****	**-0.07 (-0.13--0.01)****	0.14
In-house R&D	-0.19 (-0.49-0.1)	-0.04 (-0.33-0.25)				
No mediators			NA	NA	NA	NA
Monitoring technological developments	-0.17 (-0.36-0.01)*	-0.15 (-0.34-0.04)				
No mediators			NA	NA	NA	NA
Digital technology	**-1.25 (-1.67--0.83)****	**-1.19 (-1.68--0.71)****				
No mediators			NA	NA	NA	NA

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance (p<0.05). Only outputs and mediators with P<0.10 are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means lower autonomy.

Table A5. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and lifting heavy loads.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	**-1.15 (-1.54--0.75)****	**-1.06 (-1.5--0.62)****				
Discussion health & safety issues			**0.18 (0.07-0.29)****	**-0.67 (-1.03--0.31)****	**-0.12 (-0.22--0.02)****	0.08
In-house R&D	**-1.23 (-1.7--0.75)****	**-1.08 (-1.54--0.62)****				
No mediators			NA	NA	NA	NA
Monitoring technological developments	-0.2 (-0.52-0.12)	-0.16 (-0.48-0.16)				
No mediators			NA	NA	NA	NA
Digital technology	**-1.47 (-2.15--0.79)****	**-1 (-1.77--0.22)****				
Discussion health & safety issues			**0.57 (0.35-0.79)****	**-0.62 (-1.01--0.22)****	**-0.35 (-0.62--0.09)****	0.2
Technological and non-technological innovation			**0.39 (0.26-0.53)****	-0.58 (-1.22-0.07)*	-0.23 (-0.49-0.04)*	0.13

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance (p<0.05). Only outputs and mediators with P<0.10 are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more lifting and tiring positions.

Table A6. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and working in tiring positions

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	**-0.46 (-0.86--0.07)****	**-0.59 (-1.03--0.14)****				
Technological and non-technological innovation			**0.35 (0.27-0.44)****	**0.62 (0.06-1.18)****	**0.22 (0.01-0.42)****	0.22
In-house R&D	**-0.48 (-0.94--0.02)****	**-0.5 (-0.96--0.04)****				
No mediators			NA	NA	NA	NA
Monitoring technological developments	0.05 (-0.26-0.36)	0 (-0.32-0.32)				
No mediators			NA	NA	NA	NA
Digital technology	**-1.19 (-1.87--0.52)****	**-1.16 (-1.95--0.37)****				
No mediators			NA	NA	NA	NA

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance (p<0.05). Only outputs and mediators with P<0.10 are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more lifting and tiring positions.

Table A7. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and repetitive work.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	0.06 (-0.03-0.14)	0.02 (-0.07-0.12)				
Technological and non-technological innovation			**0.35 (0.27-0.44)****	**0.14 (0.02-0.26)****	**0.05 (0-0.09)****	0.50
In-house R&D	**-0.12 (-0.21--0.02)****	**-0.13 (-0.23--0.03)****				
No mediators			NA	NA	NA	NA
Monitoring technological developments	-0.06 (-0.12-0.01)*	**-0.08 (-0.14--0.01)****				
Technological and non-technological innovation			**0.19 (0.12-0.26)****	**0.18 (0.07-0.29)****	**0.03 (0.01-0.06)****	0.27
Digital technology	-0.03 (-0.18-0.12)	-0.05 (-0.22-0.12)				
Technological and non-technological innovation			**0.39 (0.26-0.53)****	**0.22 (0.07-0.36)****	**0.09 (0.02-0.15)****	0.29
Formal employee representation			**1.13 (0.74-1.51)****	**-0.07 (-0.13--0.01)****	**-0.07 (-0.13-0.01)****	0.25

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance (p<0.05). Only outputs and mediators with P<0.10 are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more repetitive work.

Table A8. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and repetitive work for the production sector.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	**0.24 (0.09-0.4)****	**0.23 (0.07-0.4)****				
No mediators			NA	NA	NA	NA

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance ($p<0.05$). Only outputs and mediators with $P<0.10$ are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more psychological job demands.

Table A9. Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and sitting at work.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	**1.22 (0.64-1.8)****	**1.07 (0.47-1.67)****				
Technological and non-technological innovation			**0.35 (0.27-0.44)****	**-0.86 (-1.62--0.10)****	**-0.31 (-0.57--0.023)****	0.17
Non-technological innovation only			**-0.09 (-0.14--0.04)****	**-1.52 (-2.77--0.27)****	**0.14 (0.00-0.28)****	0.08
Discussion health & safety issues			**0.18 (0.07-0.29)****	**1.02 (0.52-1.52)****	**0.18 (0.04-0.33)****	0.10
In-house R&D	**1.82 (1.25-2.39)****	**1.66 (1.14-2.18)****				
No mediators			NA	NA	NA	NA
Monitoring technological developments	0.4 (-0.06-0.87)*	0.27 (-0.16-0.70)				
Non-technological innovation only			**-0.05 (-0.09--0.01)****	**-1.59 (-2.86--0.32)****	**0.08 (-0.01-0.16)***	0.13
Formal employee representation			**0.17 (-0.02-0.36)***	**0.90 (0.67-1.13)****	0.15 (-0.03-0.33)*	0.25
Digital technology	**2.48 (1.36-3.61)****	0.78 (-0.42-1398)				
Discussion health & safety issues			**0.57 (0.35-0.79)****	**1.31 (0.69-1.94)****	**0.75 (0.29-1.21)****	0.25
Formal employee representation			**1.13 (0.74-1.51)****	**0.93 (0.59-1.27)****	**1.05 (0.52-1.57)****	0.35

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance (p<0.05). Only outputs and mediators with P<0.10 are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more sitting at work.

Table A10: Path regression coefficients (95% confidence intervals) of innovation outputs and Supportive organisational practices on the relationship between technological input and occupational risks.

Technological inputs, innovation outputs and Supportive organisational practices	Total effect c-path (input > outcome)	Direct effect c'-path (input > outcome)	a-paths (input > output)	b-paths (output > outcome)	Indirect effects a*b-path (input > output > outcome)	Proportion mediated (%)
Design products & services	**-3.38 (-5.11--1.66)****	**-2.87 (-4.78—0.97)****				
Discussion health & safety issues			**0.18 (0.07-0.29)****	**-2.45 (-4.06--0.85)****	**-0.44 (-0.85--0.04)****	0.10
In-house R&D	**-2.91 (-5.14--0.67)****	**-2.30 (-4.54--0.05)****				
No mediators			NA	NA	NA	NA
Monitoring technological developments	-0.21 (-1.59-1.17)	0.40 (-1.00-1.80)				
OSH risk management			**-0.46 (-0.71--0.2)****	**1.02 (0.45-1.56)****	**-0.46 (-0.82--0.10)****	0.35
Digital technology	**-6.49 (-9.29--3.7)****	**-4.64 (-7.84—1.45)****				
Technological & non-technological innovation			**0.39 (0.26-0.53)****	**-3.92 (-2.73—0.35)****	**-1.54 (-2.73--0.35)****	0.19

Source: Beyond 4.0 integrated database ECS- CICT/CIS/ESENER-ECWS (2013, 2014 and 2015)
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N, R and S. Differing number of sectors according to origin of variables.
Structural equation model adjusted for sector, organisational size, and region. Boldface indicates statistical significance (p<0.05). Only outputs and mediators with P<0.10 are shown. Input: higher score means more R&D and technology; output: higher score means more innovation, employee involvement and better OSH management; outcome: higher score means more occupational risks.

BEYOND 4.0

PART D - TASK 5.4
STRUCTURAL TRANSFORMATION OF WORKING TIME AND WORK-LIFE BALANCE

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Deliverable type version: D5.1 – May 2023
Associated Work Package: WP5
Lead: CNAM-CEET
WP leader: Nathalie Greenan

Status: internal

beyond4.0.eu

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 822296.

European

Document Summary

Document type:	*Deliverable D5.1 – Part C*
Title:	*Structural transformation of working time and work-life balance.*
Author/s:	*Mathis Bachelot, Rahma Bensalem, Christine Erhel, Nathalie Greenan, Mathilde Guergoat-Larivière, Malo Mofakhami, Silvia Napolitano*
Reviewer/s:	*Sylvie Hamon-Cholet*
Date:	*May 17, 2023*
Document status:	*Final*

Abstract

This report presents the main findings from TASK 5.4 (structural transformation of working time and work-life balance), in which we investigate the links between the technological transformation and socio-economic outcomes relative to working time and work-life balance.

First, we use the Beyond 4.0 integrated database ECS-LFS 2019 developed in WP3, providing improved measures of investments in technology adoption and use, the learning capacity of organisations and innovation outputs to proxy the technological transformation. The theoretical framework developed by Greenan and Napolitano (2023) is applied to this dataset to provide the latest empirical evidence about the technological transformation (Section 2). It then carries on with the analysis of the relationship between the technological transformation and quality of working time (Section 3).

Second, we use two similar linked employer-employee surveys, the British "Workplace and Employment Relations Survey" (WERS) and the French "Relations professionnelles et négociations d'entreprise" survey (REPONSE) to analyse the relationships between innovation and flexible working time arrangements and employees' work-life balance. The analysis uses individual level data from 2011 in a comparative manner and further exploration is undertaken using French data for 2017 that includes a measure of teleworking (Section 4).

Heterogeneous effects (by gender, geographical areas and skill levels) are further examined in both studies.

Content

Executive Summary

We view the technological transformation not only as the inclusion of digital technologies into the production process but also as a relationship, sometimes called the knowledge production function, which relates inputs in which firms invest with innovation outputs. Digital technologies are one of these inputs, together with R&D expenditures. We add a third input to this knowledge production function: the learning capacity of the organisation that is its ability to adapt and compete at low cost through learning. In terms of innovation output, we use the traditional distinction between product and process innovations, considered in Schumpeterian approaches as technological innovations and address marketing and organisational innovations, which are forms of non-technological innovation more often encountered in the service sector. We further examine different combinations of innovation with the idea that combinations of technological and non-technological forms of innovation reflect more advanced innovation strategies based not only on the inclusion of new technologies in the production process, but also on a revision of the organisational paradigm to better align with the set of new opportunities it opens. We then examine the relationship between the technological transformation and quality of working time issues.

A first empirical analysis grounds on data from an EU-wide combined database integrating the 2019 European Company Survey and the EU Labour Force Survey ad hoc module conducted in 2019. Data integration occurs at the level of a key cell, which is a size class (10-50 or more than 50 employees) in a 1-digit sector in a country where we aggregate information.

We find that the investment into the Learning capacity of the organisation is a win-win strategy leading to more innovativeness and to a high road of better quality of working time. Indeed, a higher Learning capacity favours all forms of innovation. In terms of combination of innovations within firms, a higher Learning capacity drives non-technological innovation only and combinations of technological and non-technological innovation, but not technological innovation only. In higher Learning capacity sectors, employees are also less exposed to low working time autonomy and involuntary part-time. There are however three points of attention associated with the Learning capacity of the organisation. First, it induces more interferences of professional life with personal life, this negative effect being partially attenuated by process and organisational innovation. Second, firms' innovation strategies have a mediating role on the effect of the Learning capacity on the quality of working time. However, these effects are most of the time partial and they do not jeopardise the overall positive effect of the Learning capacity. Product innovation reduces low working time autonomy and involuntary part-time when marketing innovation and organisational innovation augments them. Third, in most sectors, the level of the Learning capacity of the organisation has been stagnating over the last decade. Hence, barriers to the development of the Learning capacity of organisations need to be addressed.

Investments in digital technologies, meanwhile, have grown rapidly everywhere until 2019, with countries in southern, central and eastern Europe catching up with the rest of the EU. Digital technology adoption and use by sectors, as R&D and learning capacity, favours innovativeness. Higher digital intensity drives all forms of innovation. In terms of combination of innovations within firms, a higher digital intensity favours technological innovation only and combined technological and non-technological innovation, but not non-technological innovation only. Contrary to investments in the learning capacity of the organisation that generates direct impacts on working time quality, the impact of Digital technology adoption and use on working time quality is completely mediated by the innovation strategy of organisations. Product innovation mediates positively the relationship between Digital technology adoption and use and working time quality when the mediation effect of marketing innovation is opposite: it induces in digitally intensive sectors less working time quality and more work-related contacts during leisure time. Furthermore, if process innovation mediates positively the interferences of professional life with personal life, organisational innovation has a reducing impact on the relationship between Digital technology adoption and use and low working time autonomy.

A second empirical analysis uses two linked employer-employee surveys, a French one (REPONSE) and a British one (WERS) conducted in 2011, which is the last edition of WERS. The relationships between innovation, working time arrangements and work-life balance is analysed at the workplace level and results are compared between the two countries.

More specifically, after having carefully addressed the comparability issues between the two datasets, the study considers the relationship between innovation (proxied with innovation as the firm's primary strategy) and four specific working-time arrangements : non-stable working hours, substantial part-time, short part-time and long hours. France and Great Britain exemplify very different working-time regimes. However, innovation strategy has limited effects on working time arrangements in both countries. It mostly relates to a higher incidence of long working hours.

Second, the study analyses the relationship between employees' perception of work-life balance, innovation strategy and different working time arrangements. The innovation strategy does not seem to have a direct influence on employees' work-life balance in either France or the UK. On the other hand, working time arrangements have significant effects on work-life balance. Part-time work improves this balance, while long working hours worsen it. Hence, the influence of innovation strategy on work-life balance happens through its effect on long working hours.

These workplace results do not fully corroborate the meso level analysis. A main reason is that although they both cover quality of working time and work-life balance issues, these two empirical analyses use different measures. In particular, they do not approach the technological transformation in a similar way. However, the approach we have developed at a meso level could also be undertaken with linked employer/employee surveys at the workplace or company level. Such a survey covering simultaneous choices made by companies in the areas of technology and work organisation as well as employee level outcome would be the best data infrastructure to monitor the socioeconomic consequences of the technological transformation.

1. Introduction

Over the last 25 years, the working time quality component of job quality indicators has been on the rise in the EU, member states converging towards a common norm driven by EU Directives on working time that have been adopted or confirmed in national regulations (Green et al., 2013; Leschke and Watt, 2013). The 2002 EU directive concerning employee information, consultation and representation rights may also have played a role by strengthening collective voice mechanisms at the workplace level (Burdin and Pérotin, 2019). Overall, working hours have been decreasing on average and shift work at weekends and night-time has been falling.

On the other hand, working time has also become more flexible (Messenger, 2018). This global trend towards working time flexibility developed in the 1990s and 2000s and was reinforced as a way of mitigating the employment effects of the great recession or of the Covid crisis. However, the importance of working time flexibility goes beyond cyclical use and quantitative flexibility. It is also a major component of organisational policies, contributing to the efficiency of the production process. Traditional forms of flexible working time include atypical hours (working at night, in the evenings or weekends), shift work, part-time, etc.; forms that are more recent include flexible schedules as well as teleworking and mobile working.

While time management is central to the optimisation of the production process, with a potential impact on economic performance, it is also an essential dimension of the quality of life of workers, as it determines their ability to fulfil social roles other than their professional role, with a potential impact on collective well-being. Thus, there are likely to be significant trade-offs between flexibility that suits the employer and flexibility that suits the employees, with large economic and social costs at stake.

The ongoing technological transformation is likely to influence these trade-offs in many ways. As in other parts of this report, we do not view the technological transformation as the sole introduction of digital technologies into the production process, we view it as a relationship between inputs among which investment in digital technologies, but also in R&D or in the learning capacity of the organisation and innovation output. By changing the relationship with time and space, digital technologies open a large set of new organisational opportunities for employers and employees. For instance, it directly supports the development of flexible work forms based on the extension of services accessibility, on tuned management of task flows or on teleworking (Mas and Pallais, 2020). However, investing in the learning capacity of the organisation to generate new knowledge may also influence how workers interact with one another in time and space (Karasek, 2004). The innovation strategy of the organisation resulting from these joint investments may in turn influence the space and working time constraints that employers impose on employees. However, if the socio-demographic and institutional determinants (including public and private policies) of the quality and working time and work-life balance have been thoroughly investigated in quantitative studies, the empirical evidence relating the technological transformation with working time and work-life balance outcomes is scarce. One reason for this is that good quality data allowing for empirical investigation most of the time never cover these two dimensions at the same time.

This report investigates with quantitative data the links between the technological transformation and the quality of working time and work-life balance, first at the EU-wide using data aggregated at a meso level, second comparing France and Great Britain with data collected at the individual employer and employee level.

The Beyond 4.0 integrated database ECS-LFS 2019 has been developed in WP3. It combines at a meso level (sector-size-country) aggregated data from employer and employee level surveys. The 2019 European Company Survey (ECS) is used to describe the technological transformation and is integrated with the Labour Force Survey and its 2019 ad hoc module on "work organisation and working time arrangements".

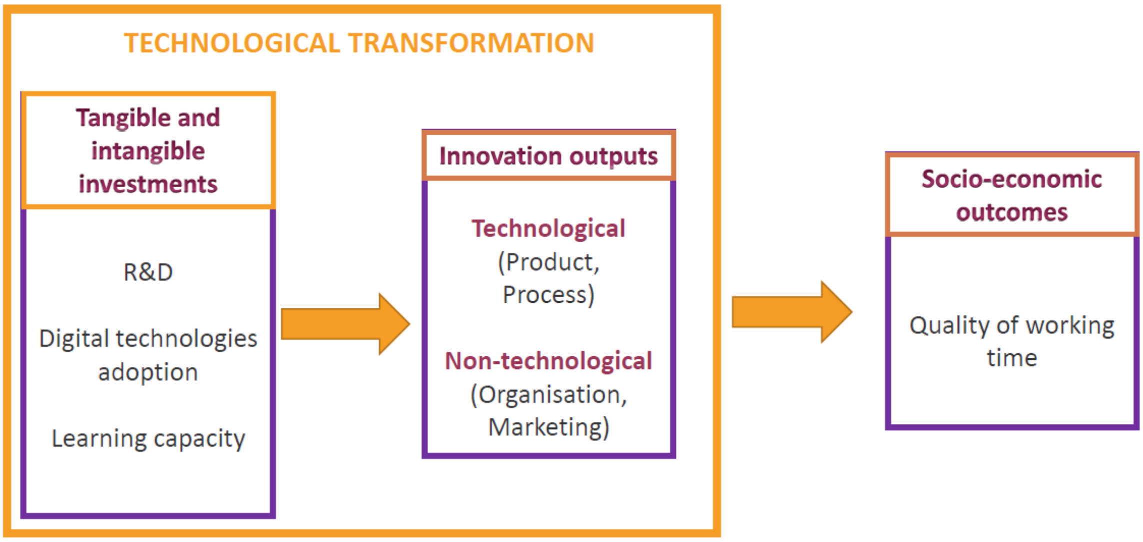
The theoretical framework developed by Greenanand Napolitano (2023) is applied to this dataset to provide the latest empirical evidence about the technological transformation. This allows including in the analysis more advanced digital technologies such as data analytics and robots (Section 2). It then carries on with the analysis of relationship between the technological transformation and quality of working time (Section 3).

This report also provides some empirical evidence based on two similar linked employer employee surveys, the British "Workplace and Employment Relations Survey" (WERS) and the French "Relations professionnelles et négociations d'entreprise" survey (REPONSE). The relationship between innovation strategies, working time arrangements and work-life balance is further explored in a comparative perspective at the workplace level.

2. Describing the technological transformation with a EU-wide combined dataset

As discussed in Greenan and Napolitano (2023) and in part D5.1A of this report, we view the technological transformation, not only as the inclusion of digital technologies into the production process but also as relationship embedded in the production process, sometimes called the knowledge production function (Crépon, Duguet, Mairesse, 1998), that relates inputs in which firms invest with innovation outputs (Figure 1). Digital technologies are one of these inputs, together with R&D expenditures.

Figure 1: Theoretical framework



We develop a composite indicator of *Digital Technology adoption and use* that takes into account the heterogeneity of ICTs and digital technologies. As we use data from the most recent years, we are able to identify emerging technologies such as robots or data analytics. We expect that investments in ICTs and digital technologies drive innovation, and we test whether this is especially true when technology investments are combined with R&D expenditure. Looking for the missing element in our current understanding of the technological transformation in the digital age, we extend the model of knowledge production function by including a third input: the *Learning capacity of the organisation* which is its ability to adapt and compete at low cost through learning. This *Learning capacity* develops with the adoption of management tools concerned with the improvement of individual and organisational learning. We aim to provide some new evidence about the relation between innovativeness, technology adoption and human and organisational capital, assuming that the *Learning capacity* is an important driver of innovation and that its combination with ICTs and digital technologies is likely to generate synergetic effects (Corrado and Hulten, 2010).

On the output side, we consider four types of innovation. We use the traditional distinction between product and process innovations, considered in Schumpeterian approaches as technological innovations and address marketing and organisational innovations, which are forms of non-technological innovation more often encountered in the service sector (OECD/Eurostat, 2005). We further examine different combinations of innovation with the idea that combinations of technological and non-technological forms of innovation reflect more advanced innovation strategies based not only on the inclusion of new technologies in the production process, but also on a revision of the organisational paradigm to better align with the set of new opportunities it opens (Bodrožić and Adler, 2018).

By using this new approach to technological transformation, we are able to consider different types of innovation strategies involving digital technologies among other inputs, with the idea that they are likely to shape socio-economic outcomes differently. In particular, we hypothesize that investing in the learning capacity of the organisation is likely to pave the way for greater innovativeness by fostering innovative work behaviour among employees (Greenan and Napolitano, 2021) while enabling a high road dynamic of improved socioeconomic outcomes (Osterman, 2018; Bailey, 2022). It overlaps with the concept of conducive economy proposed by Karasek (2004): a production process based on the development of skills at the individual and collective levels promotes both the quality of life at work and the quality of work because it generates value that contributes to the economic growth and human development of consumers. The socio-economic outcome we are going to study in relation with the technological transformation is the quality of working time. It relates to the social role of workers once their working day has ended. We would like to find out whether the technological transformation has a potential to facilitate the maintenance of the workers' social bonds.

Linking the ECS with the LFS

Our analysis builds on the construction of a cross-country and cross-sector dataset based on the integration of employer and employee level EU-wide surveys. It allows exploring the relations between company level decisions and characteristics of the economy, at a meso level (Greenan et al., 2023b). We have been gathering the most recent available data, from 2019, to cover enterprises with more than 10 employees and their employees.

At the employer level, the 2019 European Company Survey (ECS, Eurofound) covers topics related to work organisation, human resources management and social dialogue. The ECS includes questions on engagement in R&D; use of digital tools, social media, data analytics, e-commerce, software and robotisation; employees' job content, training opportunities, work organisation. It also provides data on innovation. The ECS 2019 is thus a source of data that allows describing the technological transformation. We use it to construct composite indicators measuring the enterprises' technology adoption and use, the learning capacity of the organisation and well as the innovation outputs.

At the employee level, the Labour Force Survey ad hoc modules of 2019 on "Flexibility of working time" provides indicators of the quality of working time.

Table 2: Surveys and measures of main concepts

Measures	Source of data	Level of information
R&D, engagement	European Company Survey (ECS, Eurofound), 2019	Employer
Digital technology adoption and use		
Learning capacity of the organisation		
Innovation outputs		
Quality of working time	Labour Force Survey (LFS, Eurostat) and ad-hoc module on flexibility of working time (2019)	Employee

In order to combine the two sources of data, we aggregate data and link them through a common cell, which identifies sectors within countries by size-class. The final dataset covers:

- 28 countries: the 27 EU Member States plus UK.
- 15 sectors: Nace Rev. 2 at 1-digit level, sectors B to N, plus R and S.
- 2 size classes: 10 to 50 employees and more than 50 employees.

This country coverage is smaller than the one used in the part D5.1A of the report (that also includes North-Macedonia, Norway, Serbia and Turkey), but the sector coverage is larger: in the secondary sector, mining and quarrying (B) is added and in the tertiary sector arts, entertainment and recreation industries (R) as well as other service activities (S). We have 666 cells in total. Some cells are missing because we dropped, when aggregating, cells with less than three observations to comply with criteria for anonymization, and because some sectors are not covered by all countries or do not have both size-classes.

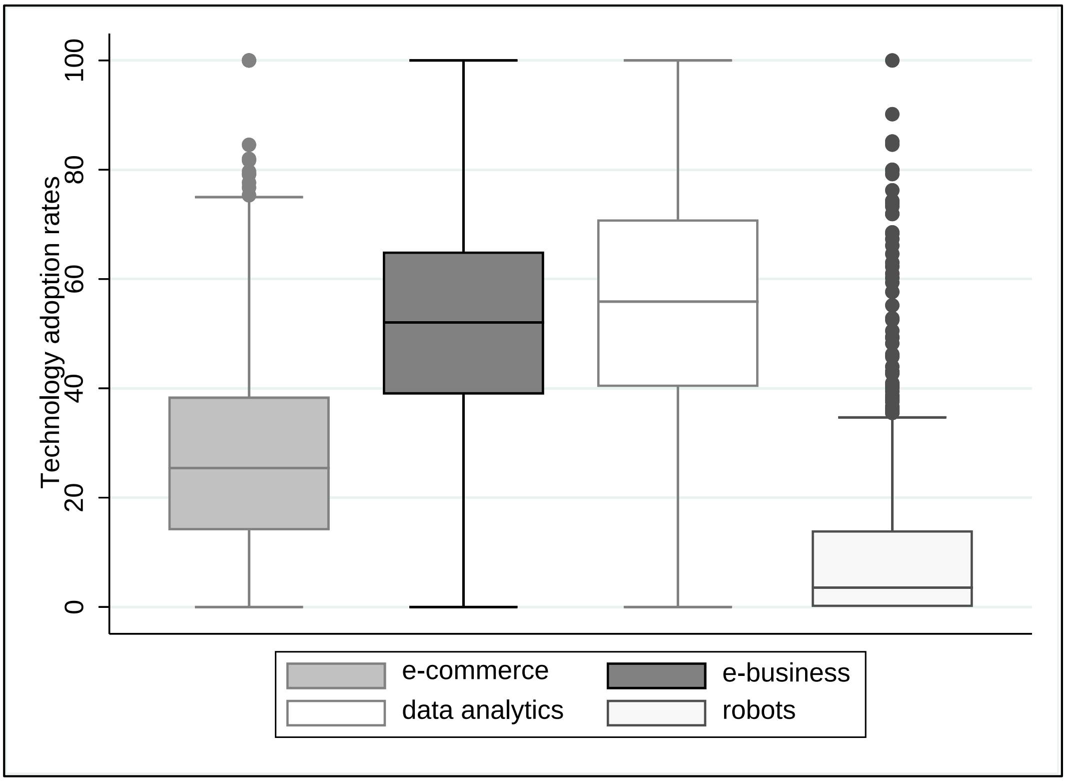
The Digital technology adoption and use indicator

The European Company Survey 2019 provides direct measures of enterprises' adoption and use of technologies, including the latest ones. We use this information to construct an indicator of *Digital technology adoption and use*. We identify four sub-dimensions in this indicator, namely e-commerce, e-business technologies, data analytics and robots (Table 4). We build a composite indicator, giving to each technology a weight equal to the inverse of its European diffusion rate, so that technologies that are more widespread have lower weights, while emerging ones have higher ones. The final indicator equals the normalised sum of the weighted rates of technology diffusion at the sector-size-country level. It varies from 0 (basic technologies adoption and use) to 1 (advanced technologies adoption and use).

Table 3: Digital technology adoption and use in the European Company Survey

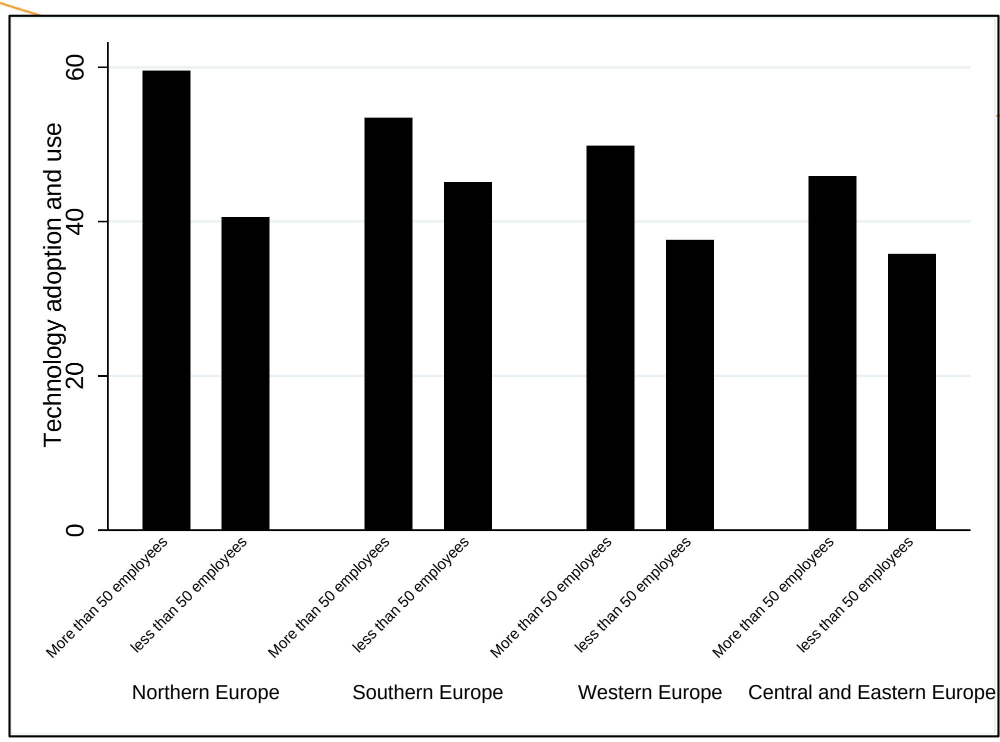
Sub-dimensions	Questions	EU diffusion rates
E-commerce	Does this establishment buy or sell goods or services on the internet? For instance, by using business-to-business portals, e-commerce etc.	28, 5%
E-business	Since the beginning of 2016, did this establishment purchase any software that was specifically developed or customised to meet the needs of the establishment?	51,5%
Data analytics	Does this establishment use data analytics (DA)? DA=1 If ITPERFMON=yes or ITPRODIMP =yes with: ITPERFMON: DA to monitor employee performance? ITPRODIMP: DA to improve the processes of production or service delivery?	55,1%
Robots	Robots are programmable machines that are capable of carrying out a complex series of actions automatically, which may include the interaction with people. Does this establishment use robots?	10,8%

Figure 2: Digital technology adoption rates in establishments across the EU



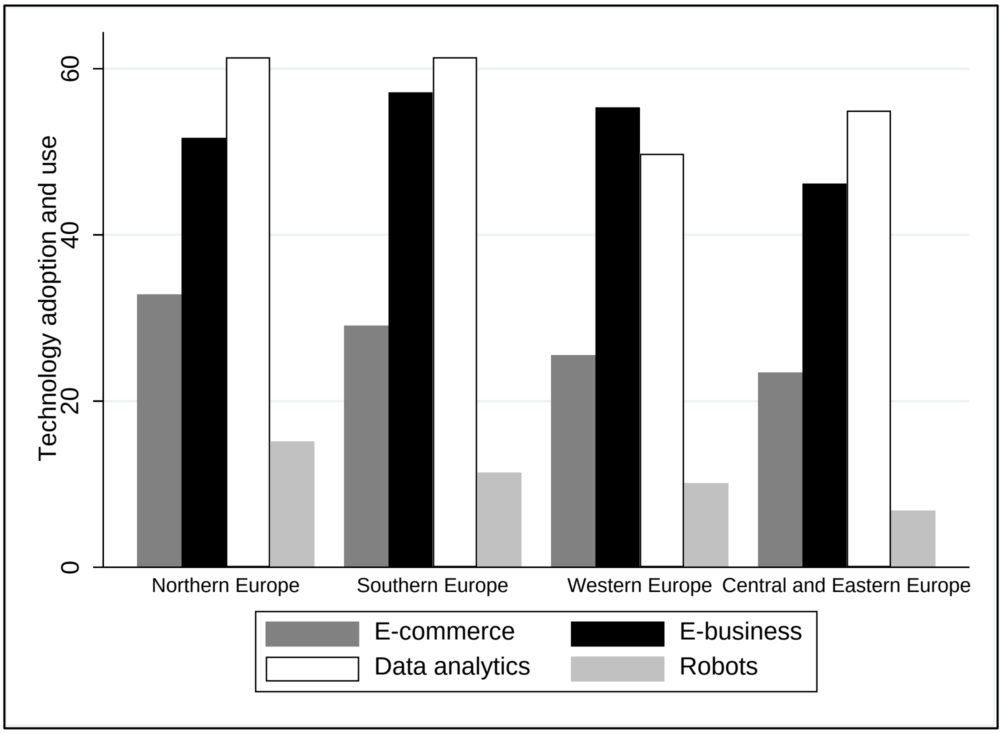
Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 3: Digital technology adoption rates by size and geographical area



Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 4: Digital technology adoption by sub-dimensions and geographical area



Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 2 shows large inequalities in diffusion of different technologies across sectors, size classes and countries. Figure 3 shows that in all regions, larger enterprises are more technologically advanced. Northern European countries have the highest levels of technologies adoption and use, while Central and Eastern Europe appears to be the geographical area with the lowest rates of technology diffusion, for all types of technologies. In Western Europe, differently from the other regions, data analytics is less diffused than e-business (Figure 4). Compared to the mapping of technology diffusion presented in part A of the report, which covers an earlier period (2010-2014) with data from the European Community survey on ICT usage and e-commerce in enterprises, we observe less inequality in diffusion between north-western Europe and the southeast. In particular, Southern Europe seems to have caught up with the West, characterised by the lowest diffusion of data analytics.

The indicator of Learning capacity of the organisation

We develop the *Learning capacity* indicator to measure the capacity of an organisation to promote management tools concerned with the improvement of individual and organisational learning. We refer to the notion of "learning organisation" defined as an entity able to adapt and compete at low cost through learning. A learning organisation is able to promote workers' individual learning by encouraging employees to develop innovative work behaviours, and then, incentivising their autonomy and discretion and promoting learning and training opportunities. Further, thanks to its organised setting, knowledge is also shared and distributed among members, an innovative culture is promoted and the trade-offs between the competing objectives of exploration and exploitation are solved through a dynamic process of strategy renewal (Greenan and Lorenz, 2010; Greenan and Napolitano, 2021).

The *Learning capacity of the organisation* indicator is constructed with employer level data from the 2019 ECS. We identify seven[1] sub-dimensions of the learning capacity of an organisation:

1. The **cognitive dimension of work**: the average of two variables, namely the percentage of employees who are required to solve unforeseen problems and learn new things;
2. **Training opportunities**: the average three variables, the percentage of employees who are in jobs that require continuous training, who participate in training sessions on the establishment premises or in other locations during paid working time and who receive on-the-job training;
3. **Autonomy** of workers: the average of two variables, namely the creation of an environment in which employees can autonomously carry out their tasks and independently organise their own time and scheduling their own tasks;
4. **Motivation backed by the organisation**: the average of three variables which are the provision to employees of opportunities for training and development, the

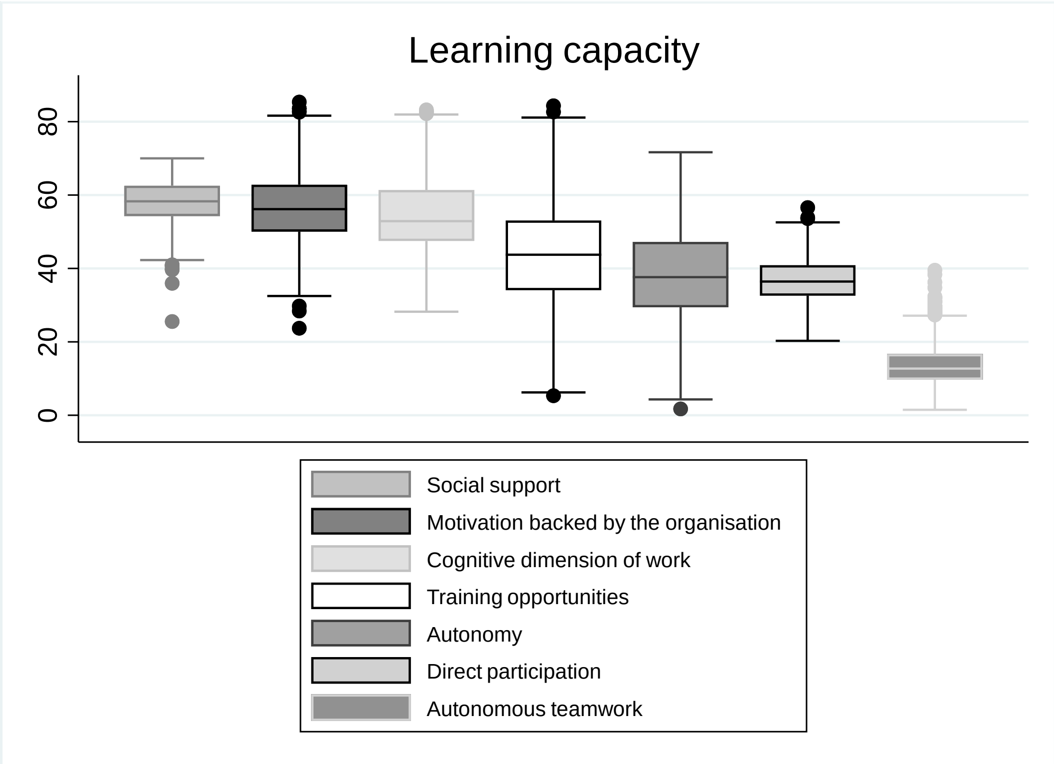
[1] The *Learning Capacity* indicator built from the European Working Conditions Survey in part A, has eight dimensions. The missing dimension is about whether the management has a supportive supervisory style. We found no indicator capturing this dimension in the ECS, probably because it is more difficult to assess it through the interview of a management representative. The other discrepancy between the two measures is in the third dimension. It is focused on the autonomy in cognitive tasks in the part A indicator when it is broader here.

communication of a strong vision and mission, providing meaning to work and the provision of an interesting and stimulation work;

5. **Autonomous teamwork**: the average of two variables, namely use of teams and whether in these teams, members decide among themselves on how tasks are distributed;
6. **Social support**: calculated from one variable, which measure whether helping colleagues without being asked is considered important;
7. **Direct participation**: the average of four variables about the use of suggestions for improving the way things are done in the company, the use of suggestion schemes, the use of meetings open to all employees and of meeting between employees and their immediate manager.

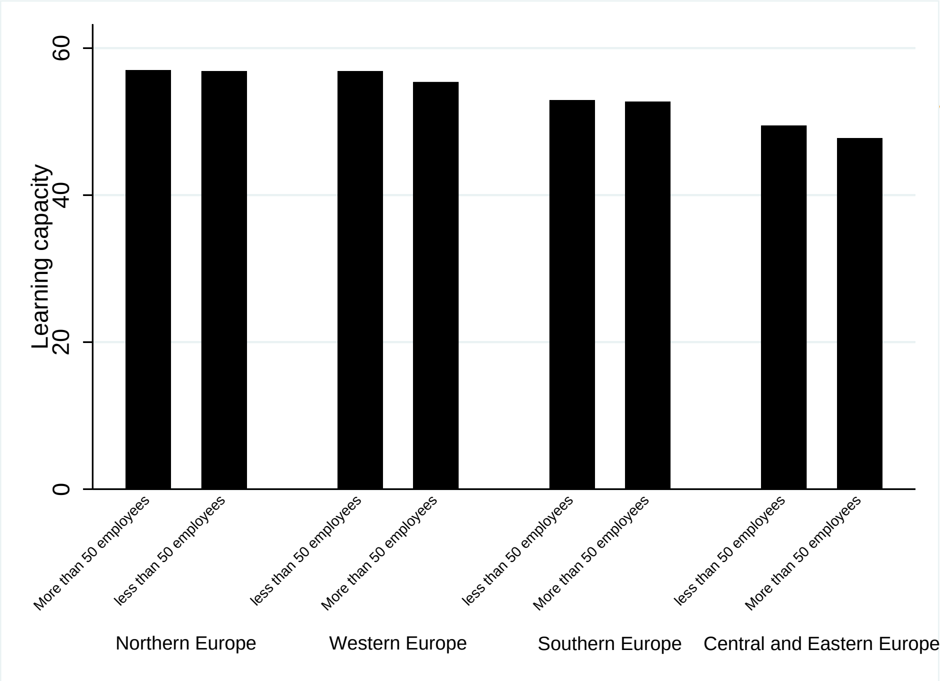
The final *Learning capacity* indicator has been constructed at the individual level as the average of the seven sub-dimensions, with equal weights in the final indicator. The composite indicator on aggregated data equals the average *Learning capacity* in a specific sector-size-country level cell. Values vary from 0 (no *Learning capacity*) to 1 (maximum *Learning capacity*). The Cronbach's alpha coefficient among sub-dimensions equals 0.83, suggesting that the items have relatively high internal consistency.

Figure 5: Spread of learning capacity in establishments across the EU



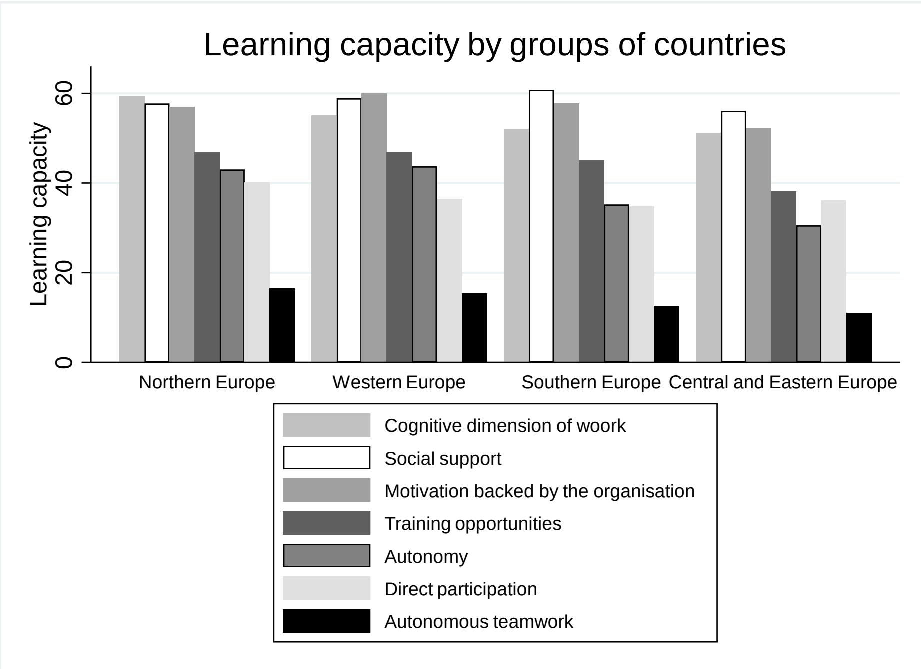
Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 6: Learning capacity indicator by size and geographical area



Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 7: Learning capacity indicator by sub-dimension and geographical area



Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 5 shows that there is great variation between different sector-size-country observations, especially concerning the training opportunities and the autonomy of worker.

Figure 6 gives the distribution of the *Learning capacity* indicator between geographical areas. It shows that *Learning capacity*, on average, does not depend on the size of the enterprise. It also shows that Northern and Western European countries have slightly higher average levels of *Learning capacity* than Central and Eastern and Southern countries. The ranking of the sub-dimensions is similar within the different groups (Figure 7). The *Learning capacity* indicator used in part A of the report is based on employee level data from the European Working Conditions Survey over 2010-2015. We therefore expect some differences with the ECS-based indicator. However, we find that they show a strong positive correlation, which confirms the idea that they address the same latent dimension. The indicators show a high dispersion between countries and sectors, their average level between geographical areas is close, and teamwork and direct employee involvement are the least frequently observed organisational practices.

The Innovation outputs

The ECS provides information on innovation outputs (Table 4). The questions on product, process and marketing innovations are similar to those asked in the Community Innovation Survey (CIS). This is not the case however for organisational innovation. In CIS, organisational innovations refer to the implementation of new organisational methods. These can be changes in business practices, in workplace organisation or in the firm's external relations.

Table 4: Innovation outputs in the European Company Survey

Sub-dimensions	Questions	EU diffusion rates
Product innovation	Since the beginning of 2016, has this establishment introduced any new or significantly changed products or services? Answer yes, whether new to the market or to the establishment	30,9%
Process innovation	Since the beginning of 2016, has this establishment introduced any new or significantly changed processes either for producing goods or supplying services? Answer yes, whether new to the market or to the establishment	32,1%
Marketing innovation	Since the beginning of 2016, has this establishment introduced any new or significantly changed marketing methods? Answer yes, whether new to the market or to the establishment	27,8%
Organisational innovation	Since the beginning of 2016 have employees directly influenced management decisions in the area of organisation and efficiency of work processes? Answer to a great extent	20,0%

In ECS, establishment are asked about how employees influenced management decisions implemented in the area of organisation and efficiency of the work process over 2016-2018. The response item includes an option to indicate that there has been no decision made in this area. We quote as an organisational innovation a situation where some decisions have been made in this area that have been influenced to a great extent by employees. The underlying concept of organisational innovation is thus more specific than the CIS one, and close to the concept of employee driven organisational innovation or workplace innovation (Oeij et al., 2015).

Econometric analysis of the technological transformation

We describe the technological transformation as the relation between the inputs of the knowledge production function and innovation outputs. As data are aggregated at the sector-size-country level (the cell), we account for the differing sizes of industries within countries by implementing a Weighted Least Squares (WLS) estimator (Wooldridge, 2010). Weights are the number of employees in the cell, with information taken from the 2019 Labour Force Survey.

We specify the following econometric models:

I. $Inno_{isj} = \beta_0 + \beta_1 R\&D_{isj} + \beta_2 Tech_{isj} + \varepsilon_{isj}$

II. $Inno_{isj} = \beta_0 + \beta_1 R\&D_{isj} + \beta_2 Tech_{isj} + \beta_3 Learn_{isj} + \varepsilon_{isj}$

III. $Inno_{isj} = \beta_0 + \beta_1 R\&D_{isj} + \beta_2 Tech_{isj} + \beta_3 Learn_{isj} + \beta_6 X_{isj} + \varepsilon_{isj}$

IV. $Inno_{isj} = \beta_0 + \beta_1 R\&D_{isj} + \beta_2 Tech_{isj} + \beta_3 Learn_{isj} + \beta_4 Learn_{isj} * Tech_{isj} + \beta_5 R\&D_{isj} * Tech_{isj} + \beta_6 X_{isj} + \varepsilon_{isj}$

Where i are sectors according to the NACE Rev. 2 classification at 1-digit level, s are the size-classes (10 to 50 employees vs more than 50 employees) and j are countries. As in Greenan and Napolitano (2023), we specify a first model by including only R&D and the indicator of *Digital technology adoption and use*. We then add the *Learning capacity indicator* in a second specification, in order to provide an augmented knowledge production function taking into account investments in organisational capital. In a third specification, we include a matrix of controls. In a fourth specification, we add the interaction terms between the *Learning capacity of the organisation* and the *Digital technology adoption and use* indicators. All specifications include country dummies, a dummy for the size-class as well as a dummy differentiating between the secondary (B to F) and tertiary (G to N plus R and S) sectors in order to control for fixed effects.

The dependent variable, $Inno_{isj}$, equals the sector-size share of enterprises in a given country that introduced an innovation of a given type. We also explore, as dependent variables, possible combinations of different types of innovation outputs, following what Eurostat does with information gathered from the Community Innovation Survey. We construct variables for technological innovation (product and/or process innovative enterprises regardless of organisation and marketing innovation; product and/or process innovative enterprises only) and non-technological innovation (organisation and/or marketing innovative enterprises regardless of product and process innovation; organisation and/or marketing innovative enterprises only) or a combination of the two (product and/or process innovative enterprises AND organisation and/or marketing innovative enterprises only) (OECD/Eurostat, 2005).

Among the independent variables, R&D is the share of establishments that engage in the design of new products or services. Tech is the *Digital technology adoption and use* indicator. Learn stands for the *Learning capacity of the organisation* indicator. X is a matrix of controls such as the share of establishments engaged in export; the share of establishments engaged in collaboration around production with one or more establishments within the company or with other companies or contracting out (ref: no collaborations); the share of establishments which had a change ownership involving a change in management, or a change in ownership without changes in management (ref: no change in ownership); the share of enterprises active for less than 10 years, between 11 and 20 years, between 21 and 30 years (ref: more than 30 years). Tables 5 and 6 show the results of the specified models, first for what concerns the different types of innovation, considered in isolation, then for combinations of technological and non-technological innovation outputs.

First, results show that engagement in R&D activities has a significant effect on innovation outputs, but with exceptions. We do not find any significance impact on organisation innovative enterprises, which is not surprising as it is an employee driven concept that underpins our measure. A 1 percentage points (pp) rise in the share of enterprises engaged in R&D increases by between 0.1 and 0.3 pp the share of innovative enterprises when only one type of innovation is considered (model III in Table 5). A second exception is the negative effect of R&D on the share of enterprises implementing combined organisational and/or marketing innovations only (Table 6). A 1 pp rise in the share of enterprises engaged in R&D increases by 0.32 pp the share of product and/or process innovative enterprises, and by 0.14 pp the share of enterprises implementing product and/or process innovations only (model III). The effect is less relevant for organisation and/or marketing innovative firms and, overall, is of 0.19 pp on the share of innovative enterprises introducing a combination of product and/or process innovations and organisation and/or marketing innovations (model III).

Digital technologies appear to be an important driver of innovations. A rise of 0.01 point in the *Digital technologies adoption and use* index has an impact, in model III, of respectively 0.26 pp, 0.32 pp and 0.35 pp for the shares of product innovative, process innovative and marketing innovative enterprises, while it has no significant relationship with the share of organisation innovative enterprises. When looking at combinations of innovations, results shows that increased *Digital technology adoption and use* has positive and significant impact on the share of product and/or process innovative enterprises (0.34 pp) and organisation and/or marketing innovative enterprises (0.38 pp), regardless any other types of innovations (model III). By contrast, for the share of product and/or process innovative enterprises only and for the share of organisation and/or marketing innovative enterprises only the effect is non-significant. When technological and non-technological innovations are combined a 0.01 point increase in *Digital technology adoption and use* has a positive impact of around 0.41 pp (model III).

Table 5: WLS with robust standard errors and number of employees as weights

	Share of Product innovative enterprises				Share of Process innovative enterprises				Share of Organisation innovative enterprises				Share of Marketing innovative enterprises			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
R&D engagement	0.388***	0.368***	0.314***	0.315***	0.313***	0.293***	0.268***	0.268***	0.0428	0.008	0.000	0.001	0.141***	0.124***	0.117***	0.118***
	(11.62)	(10.76)	(9.08)	(9.04)	(9.80)	(8.99)	(7.64)	(7.79)	(1.50)	(0.27)	(0.01)	(0.02)	(4.58)	(3.89)	(3.30)	(3.33)
Digital technology adoption and use	0.360***	0.338***	0.267***	0.262***	0.378***	0.361***	0.326***	0.309***	0.086*	0.066	0.073	0.086	0.385***	0.371***	0.356***	0.346***
	(6.21)	(5.85)	(4.30)	(4.25)	(6.29)	(6.06)	(4.85)	(4.70)	(1.77)	(1.39)	(1.35)	(1.59)	(5.94)	(5.78)	(5.03)	(4.96)
Learning capacity		0.276**	0.370***	0.364***		0.273**	0.310***	0.282**		0.488***	0.499***	0.519***		0.225*	0.236*	0.222*
		(2.40)	(3.42)	(3.34)		(2.39)	(2.61)	(2.46)		(4.78)	(4.70)	(4.92)		(1.81)	(1.81)	(1.73)
Technology x Learning				0.003				0.012**				-0.008**				0.006
				(0.71)				(2.46)				(-2.07)				(1.24)
Export sales (Ref: not applicable)																
Not engaged in export			0.181***	0.180***			0.066	0.068			-0.033	-0.033			0.096*	0.095*
			(3.68)	(3.65)			(1.16)	(1.17)			(-0.71)	(-0.72)			(1.91)	(1.89)
1% to 24%			0.324***	0.323***			0.083	0.082			-0.012	-0.015			0.112**	0.111**
			(6.40)	(6.31)			(1.49)	(1.48)			(-0.24)	(-0.30)			(2.04)	(2.04)
More than 25%			0.152***	0.154***			0.087	0.098*			-0.017	-0.027			0.047	0.053
			(2.88)	(2.86)			(1.52)	(1.67)			(-0.35)	(-0.54)			(0.91)	(1.02)
Collaboration with other Establishment (Ref. no)			-0.048	-0.047			0.016	0.019			-0.053	-0.053			-0.013	-0.012
			(-1.11)	(-1.08)			(0.30)	(0.37)			(-1.13)	(-1.13)			(-0.26)	(-0.25)
Establishment age: (Ref: >30)																
<10 years			0.001	-0.002			-0.043	-0.052			0.034	0.037			-0.014	-0.017
			(0.02)	(-0.03)			(-0.68)	(-0.82)			(0.59)	(0.65)			(-0.23)	(-0.29)
11-20 years			-0.019	-0.018			-0.031	-0.032			0.078*	0.077*			-0.002	-0.001
			(-0.36)	(-0.35)			(-0.59)	(-0.60)			(1.73)	(1.71)			(-0.04)	(-0.02)
21-30 years			-0.035	-0.033			0.020	0.025			-0.026	-0.031			-0.038	-0.035
			(-0.81)	(-0.75)			(0.36)	(0.45)			(-0.57)	(-0.68)			(-0.77)	(-0.69)
Change of ownership (Ref:No)																
Yes, with change of management			0.122	0.122			0.130	0.130			-0.064	-0.063			0.033	0.032
			(1.50)	(1.49)			(1.47)	(1.46)			(-0.95)	(-0.95)			(0.37)	(0.36)
Yes, without change of management			0.112	0.113			0.106	0.106			0.066	0.067			-0.044	-0.045
			(1.33)	(1.35)			(1.33)	(1.34)			(0.81)	(0.84)			(-0.52)	(-0.53)
Tertiary sectors	2.310*	0.899	1.342	1.427	1.022	-0.486	0.502	0.831	5.753***	2.768**	2.017	1.913	9.635***	8.381***	8.716***	8.825***
	(1.82)	(0.61)	(0.90)	(0.95)	(0.86)	(-0.36)	(0.36)	(0.60)	(5.31)	(2.36)	(1.64)	(1.54)	(7.73)	(5.95)	(5.63)	(5.72)
Size: 10 to 50 employees (ref: more than 50)	2.310*	1.602	-0.186	-0.198	-0.259	-0.989	-0.839	-0.879	4.860***	3.615***	3.104**	3.267**	-0.050	-0.655	-1.257	-1.311
	(1.78)	(1.18)	(-0.13)	(-0.14)	(-0.21)	(-0.76)	(-0.60)	(-0.63)	(4.30)	(3.15)	(2.40)	(2.54)	(-0.04)	(-0.46)	(-0.78)	(-0.82)
Constant	5.298	-5.401	-18.44*	-18.98**	-3.874	-16.36*	-24.10**	-12.33	7.071	-5.110	-13.74*	-4.424	-4.260	-12.27*	-19.11*	-16.74**
	(0.79)	(-0.67)	(-1.73)	(-2.26)	(-0.50)	(-1.67)	(-2.40)	(-1.54)	(1.17)	(-0.58)	(-1.73)	(-0.45)	(-0.63)	(-1.69)	(-1.81)	(-2.05)
Observations	664	664	664	664	664	664	664	664	664	664	664	664	664	664	664	664
Adjusted R^2	0.450	0.451	0.508	0.505	0.418	0.424	0.426	0.430	0.196	0.220	0.234	0.235	0.324	0.328	0.328	0.329

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table 6: WLS with robust standard errors and number of employees as weights

	Share of Product and/or process innovative enterprises			Share of Organisation and/or marketing innovative enterprises			Share of Product and/or process innovative enterprises only			Share of Organisation and/or marketing innovative enterprises only			Share of Product and/or process AND organisation and/or marketing innovative enterprises		
	II	III	IV	II	III	IV	II	III	IV	II	III	IV	II	III	IV
R&D engagement	0.369***	0.320***	0.320***	0.098***	0.094**	0.094**	0.172***	0.137***	0.137***	-0.099***	-0.091***	-0.092***	0.197***	0.186***	0.186***
	(10.58)	(8.78)	(8.82)	(2.90)	(2.36)	(2.36)	(6.44)	(4.73)	(4.74)	(-3.57)	(-2.94)	(-2.98)	(6.64)	(5.73)	(5.73)
Digital technology	0.434***	0.355***	0.344***	0.384***	0.378***	0.379***	0.001	-0.067	-0.070	-0.042	-0.045	-0.035	0.427***	0.419***	0.411***
adoption and use	(7.01)	(5.22)	(5.09)	(6.25)	(5.56)	(5.57)	(0.03)	(-1.32)	(-1.37)	(-0.80)	(-0.81)	(-0.64)	(7.95)	(6.90)	(6.85)
Learning capacity	0.223*	0.326***	0.311***	0.512***	0.537***	0.538***	-0.106	-0.008	-0.010	0.169*	0.196**	0.213**	0.334***	0.333***	0.320***
	(1.87)	(2.76)	(2.62)	(4.06)	(3.97)	(3.96)	(-1.09)	(-0.07)	(-0.10)	(1.86)	(2.08)	(2.25)	(2.98)	(2.85)	(2.80)
Technology x Learning			0.007			-0.000			0.001			-0.006**			0.006
			(1.56)			(-0.04)			(0.36)			(-2.01)			(1.28)
Collaboration with other		-0.042	-0.039		-0.050	-0.050		-0.047	-0.047		-0.060*	-0.061*		0.005	0.006
Establishment (Ref. no)		(-0.82)	(-0.77)		(-1.03)	(-1.03)		(-1.40)	(-1.39)		(-1.68)	(-1.72)		(0.10)	(0.13)
Export sales (Ref: not applicable)															
Not engaged in export		0.161***	0.162***		0.027	0.027		0.068	0.068		-0.069	-0.069		0.096**	0.096**
		(2.72)	(2.71)		(0.49)	(0.49)		(1.55)	(1.55)		(-1.56)	(-1.55)		(2.03)	(2.01)
1% to 24%		0.263***	0.262***		0.054	0.054		0.148***	0.148***		-0.055	-0.053		0.115**	0.115**
		(4.83)	(4.76)		(0.96)	(0.95)		(3.62)	(3.61)		(-1.37)	(-1.32)		(2.16)	(2.15)
More than 25%		0.160***	0.166***		0.011	0.011		0.119***	0.120***		-0.027	-0.034		0.039	0.046
		(2.65)	(2.68)		(0.19)	(0.18)		(2.69)	(2.67)		(-0.58)	(-0.71)		(0.76)	(0.87)
Establishment age: (Ref: >30)															
<10 years		-0.038	-0.044		0.023	0.023		-0.075*	-0.076*		-0.010	-0.006		0.040	0.035
		(-0.60)	(-0.70)		(0.37)	(0.37)		(-1.83)	(-1.84)		(-0.22)	(-0.13)		(0.74)	(0.66)
11-20 years		-0.036	-0.037		0.018	0.018		-0.051	-0.050		0.006	0.005		0.017	0.017
		(-0.66)	(-0.67)		(0.35)	(0.35)		(-1.24)	(-1.23)		(0.15)	(0.13)		(0.35)	(0.34)
21-30 years		0.050	0.053		-0.052	-0.052		0.059	0.060		-0.040	-0.043		-0.010	-0.007
		(0.94)	(0.99)		(-0.98)	(-0.98)		(1.19)	(1.20)		(-0.93)	(-1.01)		(-0.22)	(-0.16)
Change of ownership (Ref:No)															
Yes, with change of management		0.166*	0.165*		-0.0483	-0.0482		0.104	0.103		-0.111	-0.111		0.060	0.059
		(1.75)	(1.73)		(-0.62)	(-0.62)		(1.59)	(1.58)		(-1.40)	(-1.40)		(0.75)	(0.75)
Yes, without change of management		0.155*	0.156*		0.010	0.010		0.146**	0.146**		-0.004	-0.004		0.011	0.011
		(1.83)	(1.85)		(0.11)	(0.11)		(2.32)	(2.33)		(-0.06)	(-0.07)		(0.14)	(0.14)
Tertiary sectors	0.538	1.542	1.741	8.502***	8.094***	8.090***	-4.769***	-3.813***	-3.785***	3.172***	2.608**	2.497**	5.327***	5.301***	5.422***
	(0.36)	(0.99)	(1.11)	(5.61)	(4.91)	(4.87)	(-3.76)	(-2.99)	(-2.95)	(2.80)	(2.19)	(2.07)	(4.20)	(3.86)	(3.95)
Size: 10 to 50 employees	0.660	-0.425	-0.449	2.770**	2.089	2.091	-0.865	-1.163	-1.173	1.269	1.222	1.252	1.462	0.634	0.597
(ref: more than 50)	(0.47)	(-0.28)	(-0.29)	(1.99)	(1.31)	(1.31)	(-0.75)	(-1.03)	(-1.03)	(1.08)	(0.91)	(0.94)	(1.23)	(0.46)	(0.43)
Constant	0.106	-14.92*	-13.99	-9.570	-10.32	-21.11**	22.82***	14.73*	15.28**	2.487	8.758	19.40**	-22.45**	-30.12***	-29.32***
	(0.01)	(-1.67)	(-1.15)	(-1.06)	(-1.03)	(-2.05)	(3.76)	(1.78)	(2.20)	(0.46)	(1.31)	(2.41)	(-2.53)	(-3.58)	(-3.52)
Observations	664	664	664	664	664	664	664	664	664	664	664	664	664	664	664
Adjusted R^2	0.479	0.521	0.519	0.358	0.355	0.354	0.186	0.240	0.238	0.115	0.122	0.125	0.424	0.430	0.431

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

The index for the *Learning capacity of the organisation* captures a strong driving factor of innovation which is missing in usual models. It is hence a central feature of the technological transformation. The comparisons between model I and II shows that the indicator adds information to the analysis, without altering substantially R&D and *Digital technology adoption and use* coefficients. The significant and positive effect of the *Learning capacity* indicator shows that innovation also depends on having forms of work organisation favouring innovative work behaviour and creativity throughout the whole workforce. The *Learning capacity of the organisation* is significant for all types of innovative enterprises, but it is especially relevant for the share of organisation innovative enterprises, with an impact of around 0.5 pp for a 0.01-point increase (model III). It also favours an increase in the share of product innovative enterprises (0.37 pp), process innovative enterprises (0.31 pp) and, but less significantly, marketing innovative enterprises (0.23 pp). As well, it fosters combinations of innovations: a 0.01-point increase in *Learning capacity* has a significant and positive impact of around 0.31 pp on product and/or process innovative enterprises and of 0.53 pp on organisation and/or marketing innovative enterprises (regardless any other form of innovation). As well, it shows a positive effect on combination of technological and non-technological innovations, with an effect of 0.32 pp. It shows a significant effect of 0.17 pp on non-technological innovations only, while it is not significant for the share of technological innovative enterprises only (model III).

While the results concerning R&D, *Digital technology adoption and use* and the *Learning capacity of the organisation* are consistent with what we found on a different dataset, the Beyond 4.0 integrated database CIS-CICT-ECWS (2010, 2012 and 2014) (see part A and Greenan and Napolitano, 2023), results about the interaction term between *Digital technologies* and *Learning capacity* investments (Model IV) shows some differences. The interaction term has a lower significance. It is positively associated only with the share of process innovative enterprises, while it is negatively associated with the organisation innovative enterprises. It has no significance when combinations of technological and non-technological innovations are considered, with the exception of non-technological innovative enterprises only, for which the effect of the interaction term is negative, but close to zero. These differences could come from the more recent time period and emerging technologies covered, from the fact that the *Learning capacity indicator* is measured with an employer rather than an employee survey and from the different concept of organisational innovation underlying the ECS measure. While the *Learning capacity of the organisation* clearly increases the odds of bottom-up organisational innovation, participative employees do not seem to get extra creativity from the use of *Digital technologies*.

3. Quality of working time as an outcome of the technological transformation

In this section, we are going to relate the technological transformation as measured with the knowledge production function with a set of outcomes related with the quality of working time.

3.1 Measuring quality of working time

The Labour Force Survey (LFS) and its 2019 ad-hoc module allow us approaching the quality of working time through different indicators.

Table 5: Quality of working time outcomes

Source	Indicator	Variables	Description
LFS 2019 ad hoc module	Low working time autonomy : time schedule	Variwt	It varies from 0 (high working time autonomy: worker can fully decide by himself on the start and end of working time) to 1 (low working time autonomy: employer or organisation mainly decides)
	Low working time autonomy : hours off	Freehour Variwt	It varies between 0 (high working time autonomy: worker can fully decide working time) and 1 (low working time autonomy; very difficult to take one or two hours off for family or personal matters within one working day).
	Required change in working time	Flexwt	It varies between 0 (no change in working time required by tasks, clients or superiors) to 1 (frequent required change in working time)
	Contacted on work matter	Avaifree	We reverted the scale to obtain an ordinal variable and we standardized it so it varies between 0 and 1 from the most frequently contacted on work matters during leisure time to the least frequently contacted.
LFS 2019	Involuntary part-time	FTPT Wish-more	We extracted the share of employees who wants to work more out of "wishmore" and we crossed it with the percentage of part-time workers out of "FTPT". We obtained a score that varies between 0 and 1 indicating the share of involuntary part-time workers.
	Long working hours (48+)	Hwactual	Worked more than 48 hours the reference week
	Working from home	Homewk	It varies between 0 (person never works home) to and 1 (person usually works home)

Thanks to these data, we are able to take into account the fact that employed workers have other social roles to fulfil than the one linked to their sole professional activity. A higher working time quality facilitates a more harmonious arrangement of the different social times, which is likely to lead to the feeling of improved work life balance. In the following, we are going to invert the scale of working time quality in order to capture adverse working time outcomes for employees (Table 5).

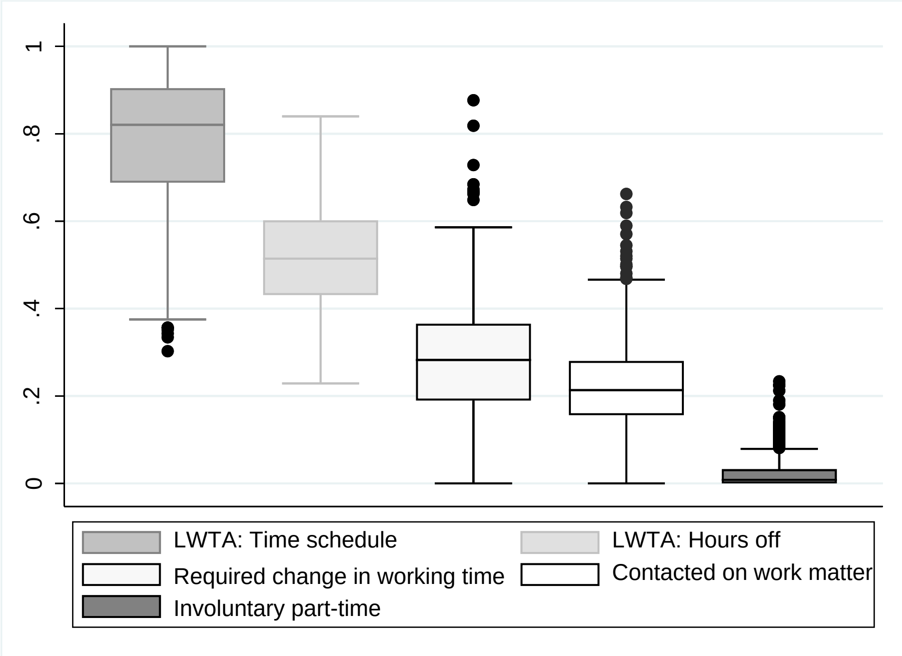
We first consider two indicators of flexibility of working time arrangement that benefit to the employee, thus reflecting the level of working time autonomy. The first one indicates whether employees are able to decide themselves on the start and end time of the working day and the second one whether they can easily take one or two hours off within a working day for family or personal matters. The indicators we built from these variables identify situations of low working time autonomy in deciding on time schedule or on taking hours off.

We then address working situations where the personal life of employees is exposed to professional contingencies. This is captured with another pair of indicators. The first one tells whether employees have to make frequent change to their working time required by tasks, clients or superiors and the second one indicates whether employees are frequently contacted on work matters during their leisure time.

The core questionnaire of the LFS provides further information to grasp low working time quality situations. The usual working hours allow computing the share of employees working more than 48 hours a week. We can also measure the share of employees who frequently work from home. If it is connected with reconciliation between personal and professional life, it is however difficult to value this work situation as positive or negative for employees. The results for long working hours and for working from home are given in the appendix because, as we will see, these two outcomes behave differently in our econometric analysis. From the LFS we also keep as indicator of low working time quality the share of part-time workers who want a full time job.

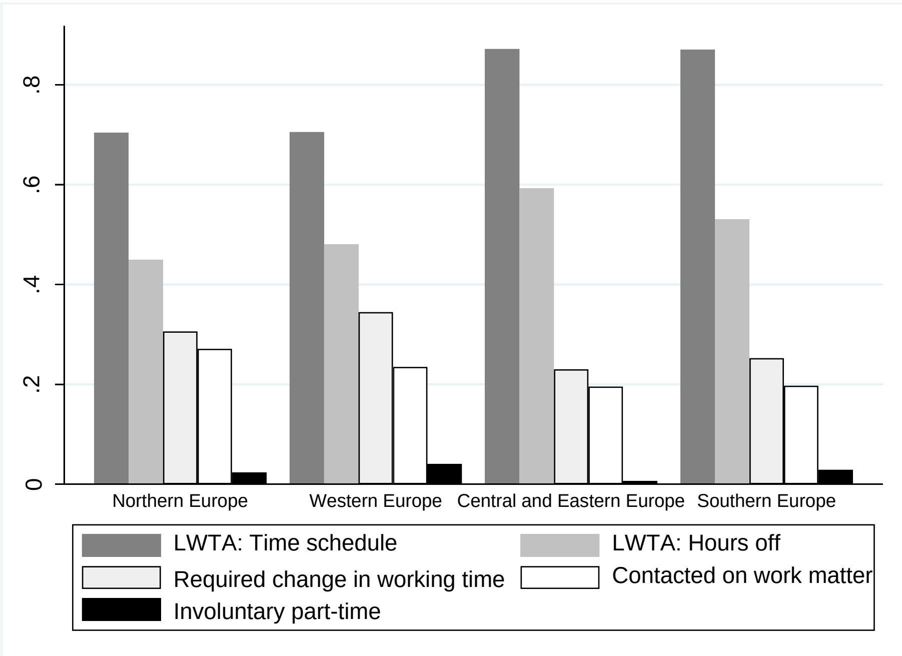
Figures 8, 9 and 10 provide descriptive statistics about these outcomes. Figure 8 shows that low working time autonomy is the most frequent situation followed by exposures of personal life to professional life. Involuntary part-time work remains overall at a low level. Figure 9 shows that the outcomes distribution follows the same pattern in every region of Europe. There are almost no differences between the Northern and Western geographical areas. The involuntary part-time is very low for the Central and Eastern Europe compared to the other regions. As working time quality and work life balance issues are gendered, Figure 10 shows the outcomes' breakdown by gender. We do not find any significant difference for low working time autonomy. At the same time, women are less likely than men to have their personal life exposed to professional contingencies, consistently with the conclusions of Magda and Lipowska (2022) who use the same survey. Finally, as expected, we observe that men are less exposed to involuntary part-time work.

Figure 8: Spread of working time quality and WLB indicators across the EU



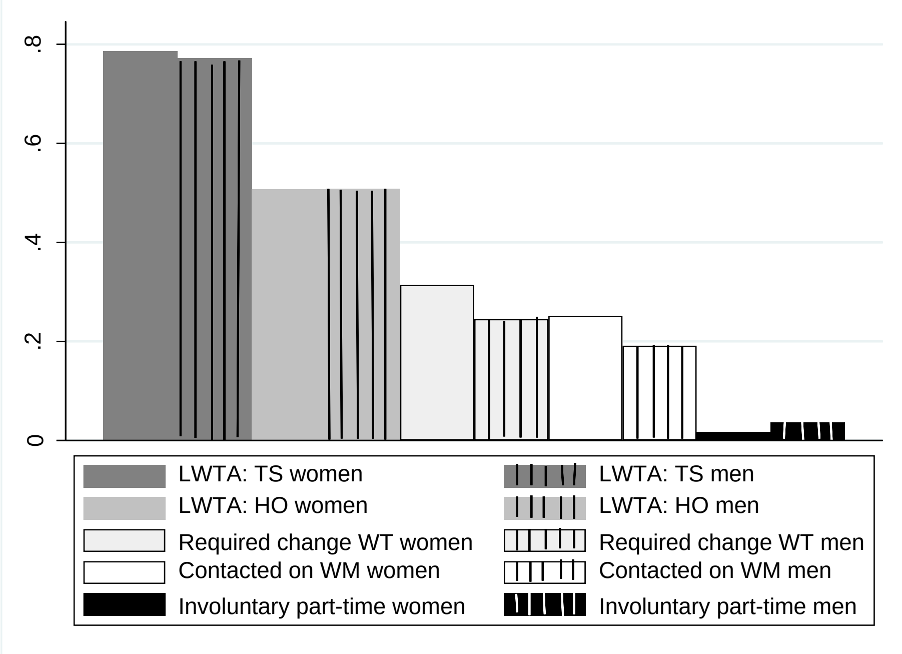
Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 9 Working time quality and WLB by geographical area



Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 10: Working time quality and WLB by gender



Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

3.2 Econometric model

We are going to analyse econometrically the relationship between the technological transformation and working time quality. Table A1 in the appendix gives the correlation matrix among the variables of interest we use in the model and Table A2 gives descriptive statistics for inputs, outputs and working time outcomes on the overall size-sector-country cells and broken down by sector groups and geographical areas.

We first estimate weighted least squares regressions, as we did in the section 2, to test the relationship between inputs, innovation outputs and the working time outcomes. Results are reported in Tables A3 to A6 in the appendix.

In this section, we present results from the implementation of a Structural Equation Model (SEM). Differently from the weighted least squares, it allows to estimate simultaneously the multiple relations between the inputs of the knowledge production function and the innovation outputs and between the inputs, the outputs and the working time outcomes.

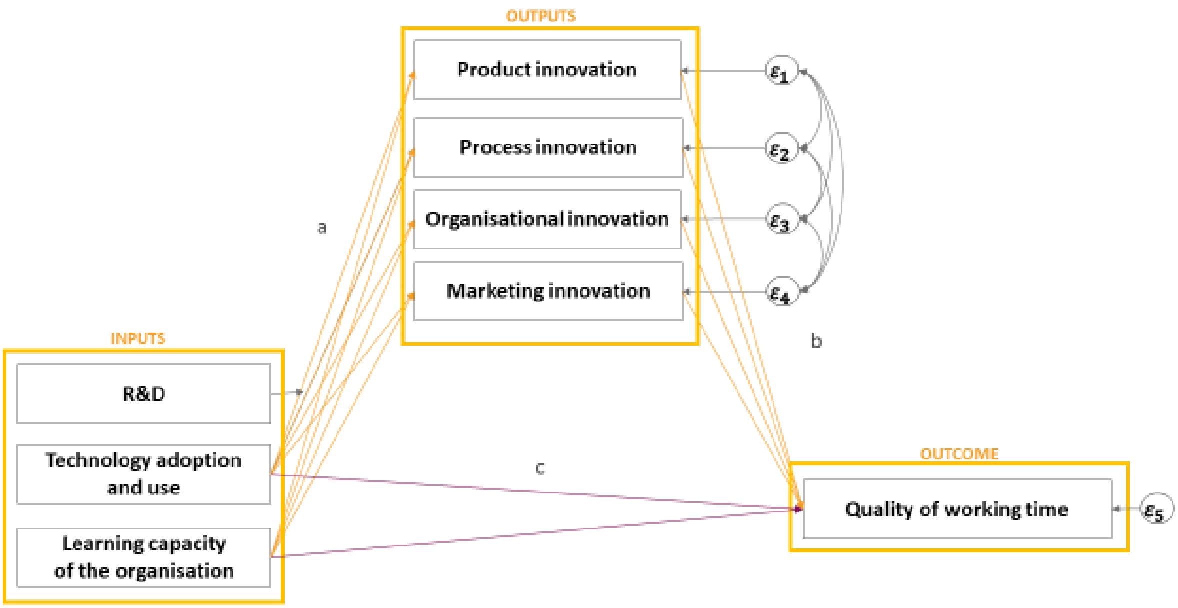
Our system includes the following equations:

$$\begin{cases} Product\ Inno_{ijs} = \beta_0 + \beta_1 R\&D_{ijs} + \beta_2 Tech_{ijs} + \beta_3 Learn_{ijs} + \varepsilon_{ijs} \\ Process\_Inno_{ijs} = \beta_0 + \beta_1 R\&D_{ijs} + \beta_2 Tech_{ijs} + \beta_3 Learn_{ijs} + \varepsilon_{ijs} \\ Organisation\_Inno_{ijs} = \beta_0 + \beta_1 R\&D_{ijs} + \beta_2 Tech_{ijs} + \beta_3 Learn_{ijs} + \varepsilon_{ijs} \\ Marketing\_Inno_{ijs} = \beta_0 + \beta_1 R\&D_{ijs} + \beta_2 Tech_{ijs} + \beta_3 Learn_{ijs} + \varepsilon_{ijs} \\ \\ Outcome_{ijs} = \beta_0 + \beta_1 Tech_{ijs} + \beta_2 Learn_{ijs} + X(Inno - type)_{ijs} + \varepsilon_{ijs} \end{cases}$$

Where i are sectors according to the NACE Rev. 2 classification at 1-digit level, j are countries and s are the size-classes (10 to 50 employees vs more than 50 employees). The first set of regressions describes the technological transformation. The variables $Inno_{ijt}$ represent the sector level share of enterprises in a given size-class and country that introduced new or significantly improved products or services, production processes, organisational methods, marketing concepts or strategies. We specify the most parsimonious model among the different specifications that we tested in the previous section. We thus include the *Digital technology adoption and use* indicator and the *Learning capacity indicator* as inputs and R&D engagement as an independent variable. The results of this first part of the model are similar to the ones presented and discussed in section 2.

In this section, we are going to present the results of the last regression that analyses the relationship between the technological transformation and each of the outcomes we consider. In this outcome regression, we include the *Digital technology adoption and use* and the *Learning capacity of the organisation* indicators which we expect to interact directly with working time outcomes as well as the four innovation types that are the dependent variables in the first set of regressions. All specifications are controlled for geographical area, a dummy distinguishing between tertiary and secondary sectors and a dummy distinguishing small enterprises (10 to 50 employees) from larger one (more than 50 employees).

Figure 11: The Structural Equation Model scheme



The SEM model represented in Figure 11 allows to conduct a mediation analysis that checks whether the relationships between the selected inputs of the technological transformation and working time quality are mediated by the innovation strategies of firms reflected in the innovation outputs of our model. As a result, the influence of inputs on outcomes equals the sum of indirect (through innovation outputs) and direct effects.

The RIT test provides the effect size of an indirect effect as the ratio of the indirect effect to the total effect, as in the following formula:

$$RIT = \frac{a * b}{(a * \ b\ ) + c}$$

Where "c" is the direct effect between an inputs and an outcome, "a" the indirect effect between the input and the innovation outputs and "b" the indirect effect between the innovation outputs and the outcome. Following MacKinnon et al. (2007), the RIT value can be interpreted as the percentage of the effect of an independent variable (e.g. *Learning capacity*) on the dependent variable (working time autonomy) mediated by the innovation output variable (e.g. product innovation).

3.3 Results

We ran the SEM model on five working time outcomes: the two working time autonomy indicators, the two indicators of exposure of personal life to professional life, and the involuntary part-time work indicator.

As mentioned in the previous section, we also considered long working hours (more than 48 hours a week) and working from home. We did not find any mediation effects of innovation outputs in the SEM regressions for these two additional outcomes. In Table A6 in appendix we give the results of the Weighted Least Square regressions. We find some direct effects of the *Digital technology adoption and use* and the *Learning capacity of the organisation* indicators depending on the outcome. *Digital technologies* are associated with less long working hours and they are not significantly related with working from home whereas the *Learning capacity of the organisations* is associated with working more frequently from home and has no significant impact on long working hours. Further, we find no significant interaction effect between the two inputs and these outcomes.

It is widely acknowledged that digital technologies have the potential to blur the time and space boundaries of the working day, possibly pushing towards longer working hours and more frequent working from home (Greenan et al., 2020, Wacjman, 2015). Our results are thus unexpected. The fact that the inputs of the technological transformation are either unrelated or negatively related with long working is however a first favourable assessment on the consequences of the technological transformation on working time quality. The finding that working from home is not significantly related with the adoption and use of digital technologies reveals that, in the period prior to the Covid crisis, highly digitalised work environments did not particularly exploit the remote working opportunities offered by digital technologies. Rather, the blurring of the spatial norm of work appears positively related with form of work organisation. The investment in the production of new knowledge through the development of the individual and collective learning capacities is positively related with a higher incidence of working from home.

The results of the SEM models for our five outcomes are presented in Table 6, followed by a set of graphs (Figure 12 to Figure 14) showing the direct and indirect effects of the *Digital technologies adoption and use* and *Learning capacity* indicators. A first outstanding result of the SEM regressions is that there are no direct relationships between the *Digital technology adoption and use* indicator and the selected outcomes. This is clear evidence that there is no deterministic relationship between use of digital technologies and working time quality. The mediation analysis presented below tests the indirect influences of the adoption and use of digital technologies on the quality of working time, i.e. via companies' innovation strategy.

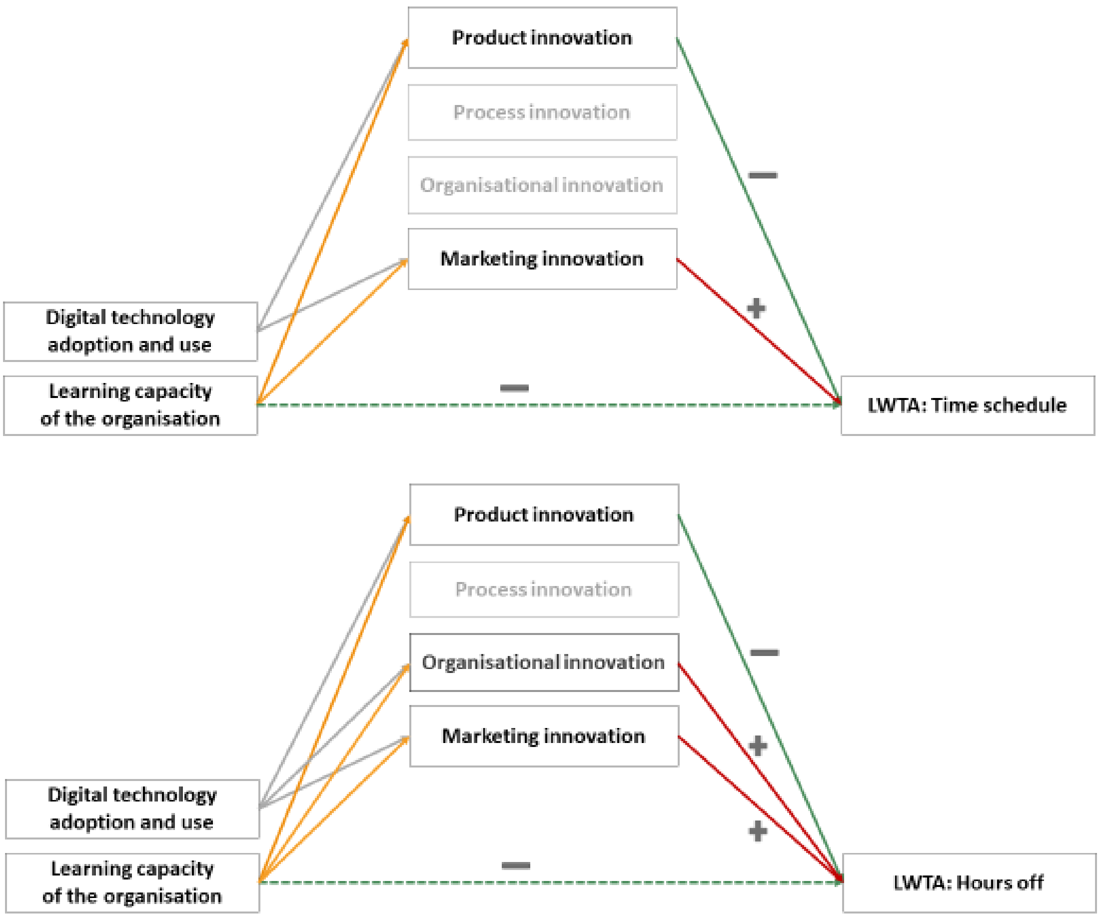
By contrast, the *Learning capacity* indicator has some direct effects on our five working time outcomes. It is associated with a lower incidence of low working time autonomy, with more exposure of personal life to professional life and with less involuntary part-time work. We may also recall that a direct positive effect was found with working from home. The mediation analysis presented below allows checking whether these mixed effects are partially mediated by the innovation strategy of firms.

Table 6: SEM regression on total population

	LWTA: Time Schedule	LWTA: Hours off	Required change in working time	Contacted on work matter	Involuntary part-time work
Digital technology adoption and use	0.002 (0.05)	-0.009 (-0.29)	-0.039 (-1.08)	-0.029 (-0.92)	0.010 (0.85)
Learning capacity	**-0.934***** (-16.89)	**-0.768***** (-17.15)	**0.454***** (7.29)	**0.518***** (10.13)	**-0.063***** (-3.82)
Share of product innovative enterprises	**-0.092***** (-3.06)	**-0.094***** (-3.82)	**0.051*** (1.67)	-0.023 (-0.94)	**-0.022**** (-2.34)
Share of process innovative enterprises	0.014 (0.46)	0.023 (0.92)	**-0.076**** (-2.35)	**-0.055**** (-2.13)	-0.007 (-0.59)
Share of marketing innovative enterprises	**0.081***** (2.86)	**0.0703***** (3.33)	-0.002 (-0.08)	**0.054**** (2.37)	**0.026***** (2.76)
Share of organisational innovative enterprises	0.050 (1.62)	**0.0673***** (2.62)	**-0.082***** (-2.79)	-0.034 (-1.25)	**0.025***** (2.84)
Tertiary sectors (Ref:secondary sectors)	-0.013 (-1.52)	**0.0150*** (1.89)	**0.041***** (4.18)	0.007 (0.91)	**0.025***** (11.47)
Small enterprises (Ref: enterprises 50+)	-0.008 (-1.02)	0.000 (-0.01)	-0.010 (-1.06)	-0.007 (-1.03)	**-0.010***** (-3.59)
Region (Ref :South EU) Northern Europe	**-0.132***** (-11.24)	**-0.057***** (-5.72)	**0.036***** (2.69)	**0.052***** (4.66)	**-0.007*** (-1.72)
Western Europe	**-0.133***** (-13.06)	**-0.027***** (-3.24)	**0.066***** (5.73)	0.011 (1.27)	**0.011***** (2.77)
Central-Eastern Europe	**-0.037***** (-3.90)	**0.028***** (2.82)	-0.011 (-0.88)	0.013 (1.53)	**-0.026***** (-7.42)
Constant	**1.369***** (50.15)	**0.921***** (43.78)	0.037 (1.24)	**-0.043*** (-1.73)	**0.044***** (4.94)
Observations R^2	662 0.82	662 0.79	662 0.71	662 0.71	662 0.71

*T statistics in parentheses, *p<0.10, **p<0.05, ***p<0.010*
Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S

Figure 12: Direct and indirect relationships via outputs between inputs and low working time autonomy (LWTA) concerning time schedule and possibilities to take hours off

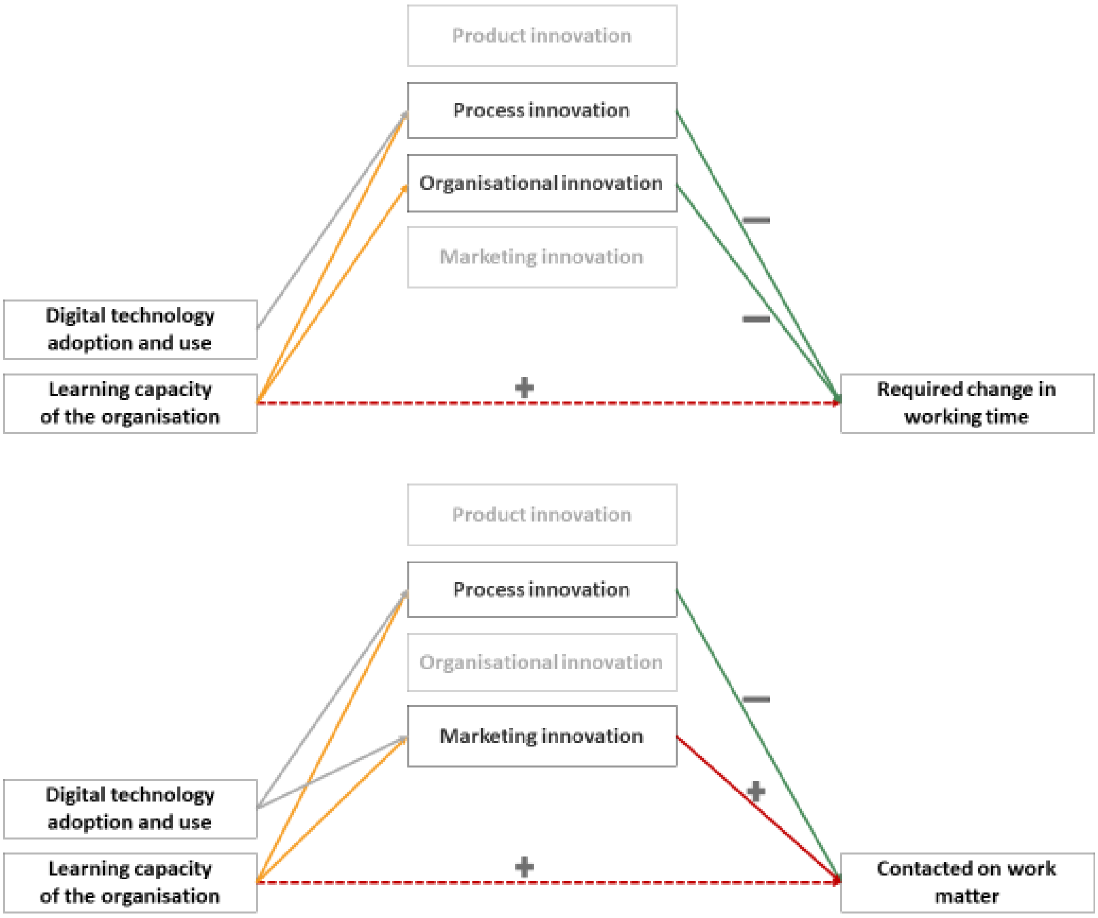


Note: The figure reports only relationships relevant for the analysis of the outcome. A dotted line indicates a direct relationship between inputs and outcomes ("c" type effect), solid lines indicate indirect effects ("a" and "b" type effects). A light grey innovation type box in the middle of the figure indicates no mediation effect. "a" types effects correspond to full mediation when the line is grey, partial when it is orange. "b" type effect leads to a favourable outcome when the line is green, to an unfavourable one when it is red.

Coefficients associated with the shares of the different innovation types in Table 6 gives a first idea of how innovation outputs influence the working time outcomes. We observe that product and process innovations have positive consequences by being associated for the former with reduced low working time autonomy and involuntary part-time work and for the latter with reduced exposure of personal life to professional life.

On the contrary, marketing innovation favours adverse working time outcomes. It relates positively with low working time autonomy, contacts on work matters during leisure time and involuntary part-time work. Finally, employee driven organisational innovation displays ambiguous relationships with the quality of working time. It has a positive influence through a lower incidence of changes required by the employer concerning the organisation of working time. But we also find evidence of lower working time autonomy and higher involuntary part-time work.

Figure 13: Direct and indirect relationships via outputs between inputs and interferences of professional life on personal life

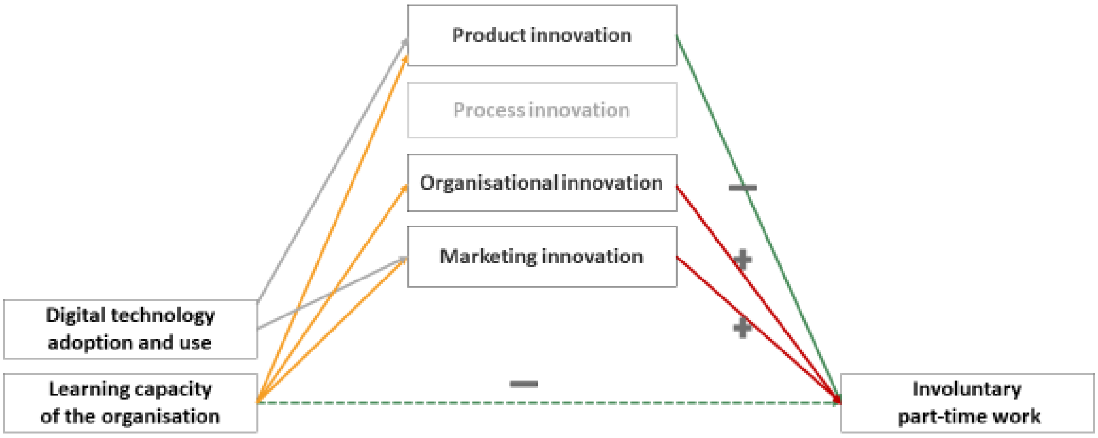


Note: The figure reports only relationships relevant for the analysis of the outcome. A dotted line indicates a direct relationship between inputs and outcomes ("c" type effect), solid lines indicate indirect effects ("a" and "b" type effects). A light grey innovation type box in the middle of the figure indicates no mediation effect. "a" types effects correspond to full mediation when the line is grey, partial when it is orange. "b" type effect leads to a favourable outcome when the line is green, to an unfavourable one when it is red.

Figure 12 shows that the influence of investment in Digital technologies on working time autonomy is totally mediated by firms' innovation strategies. Product innovation promotes autonomy, while marketing innovation reduces it. Organisational innovation has also a negative mediating effect on working time autonomy, but limited to the possibility of taking time off during the working day. The influence of the Learning capacity of the organisation, on the other hand, is only partially mediated by innovation. Product innovation makes a contribution of 2% (according to the RIT test) to the positive relationship between the Learning capacity and autonomy in deciding on the start an end of the working day, and 3% to the ability to take time off for family or personal reasons. Marketing innovation and organisational innovation slightly attenuate the protective effect of the Learning capacity of the organisation on low working time autonomy (RIT of 2% and 4% respectively).

Figure 13 shows again that investments in *Digital technologies adoption and use* have an influence on interferences between professional and personal life, which is fully mediated by types of innovation when the *Learning capacity of the organisation* has a direct impact, which is partially mediated by innovation. Indeed, higher *Learning capacity of the organisation* goes with more interferences, both in the form of changes in working time required by the employer and professional contacts between leisure time. Process innovation has an attenuating impact on both type of interferences (RIT for *Learning capacity* of respectively 3% and 2%), probably by increasing the reliability of the production process while organisational innovation limits the first type of interference (RIT for *Learning capacity* of 8%). Furthermore, marketing innovation mediates positively both inputs by favouring more contact on work matters during leisure time (RIT of 2% for the *Learning capacity*).

Figure 14: Direct and indirect relationships via outputs between inputs and involuntary part-time work



Note: The figure reports only relationships relevant for the analysis of the outcome. A dotted line indicates a direct relationship between inputs and outcomes ("c" type effect), solid lines indicate indirect effects ("a" and "b" type effects). A light grey innovation type box in the middle of the figure indicates no mediation effect. "a" types effects correspond to full mediation when the line is grey, partial when it is orange. "b" type effect leads to a favourable outcome when the line is green, to an unfavourable one when it is red.

The same pattern of full mediation for *Digital technology* and partial mediation for the *Learning capacity* characterises the relationship between the technological transformation and involuntary part-time work (Figure 14). The direct effect of the *Learning capacity of the organisation* is negative thus limiting the incidence of this non-standard form of work. Product innovation has a similar influence while marketing and organisational innovation favour involuntary part-time work. *Digital technology adoption and use* is fully mediated by product and marketing innovation, which have opposite influences, while the *Learning capacity of the organisation* is partially mediated by the three forms of innovation (RIT of 9%, 9% and 19% respectively).

Heterogeneous effects by gender and geographical areas

We widen the analysis by including first, the gender aspect and second, geographical heterogeneities.

Indeed, gender can lead to more difficulties when it comes to the quality of working time and work-life balance. We thus want to establish if *Digital technology adoption and use* and

Learning capacity influence differently the quality of working time of women and men. To this aim, we run the same econometric model as in the previous section, but tested on outcomes measured on subsamples of women and men, respectively. This means that the outcomes represent, for example, the percentage of female employees that has low working time autonomy.

The results are displayed in Table 7. A common feature for both gender is that we find, like on the overall population no direct effect of *Digital technology adoption and use*, while we do observe direct effects of the *Learning capacity of the organisation*. If the signs of the effects are the same as on the overall population, we note however some differences between genders in the size of the coefficient associated with the *Learning capacity*. The reduction of low working time autonomy associated with it is larger for men than for women. In terms of interferences between professional and personal life, comparisons show that the *Learning capacity of the organisation* is more strongly associated with the employer requiring women some changes in their working time and contacting men on their leisure time. Finally, it has a stronger impact on reducing involuntary part-time for women than for men.

Another gender difference is in the mediating role of innovation which appears mainly driven by male working time outcomes. This is because the share of the different types of innovative firms has a weaker and less significant impact on working time quality for females. The only significant mediation effects concerning females are unfavourable. They concern the possibility of taking hours of from work for family or personal reasons and involuntary part time work. Marketing and organisational innovation attenuate the protective effect of the *Learning capacity* on the possibility of taking hours off and drive investments into *Digital technologies* towards less working time autonomy. We observe a similar mediating role of organisational innovation on the development of involuntary part-time work. Males are also at a disadvantage with regard to both outcomes in the presence of organisational and marketing innovations. But they benefit from the positive mediating role of product innovation on working time autonomy and on involuntary part time and of process innovation on employer-required changes in working time, whereas women do not. However, they suffer more from marketing innovation as it mediates negatively for them the relationship between investments in *Digital technologies* and *Learning capacity* and the ability to decide on when to start and end the working day, the fact of being contacted on work matters during leisure time and involuntary part-time work.

As we find significant differences in the technological development between different European regions and in particular between Northern and Western countries vs Southern, Central and Eastern countries, we also run the models on the subsample of observations in these two geographical areas. Outcomes are measured as in the whole population. The results of the regressions are displayed in Table 8.

The pattern found in the overall population of no direct effect of *Digital technology adoption and use* while such effects are observed of the *Learning capacity of the organisation,* holds here again in our two sub-groups of region with two exceptions: in the South-East, we observe a direct effect of *Digital technologies adoption and use* on the possibility to choose the start and end time of the working day when in the North-West the direct effect of the *Learning capacity* on involuntary part-time work is not significant. Like in the case of the comparison between gender, if the direct effect of the *Learning capacity of the organisation* on working time quality outcomes keep the same sign, we observe differences in the size of coefficients: they are much stronger in the North/West compared with the South/East for the autonomy in the choice of time schedule and for the fact of being contacted on work matters during leisure time.

The coefficients for the impact of shares of innovative enterprises according to their type also show some large differences between geographical areas, leading to specific regional mediation patterns.

In the South/East, we find no mediation pattern of innovation for the fact of being contacted on leisure time for work matters. The share of product innovative enterprises mediates in a favourable way the relationship between *Digital technologies* and *Learning capacity* and the two types of working time autonomy considered. The other favourable mediation effect concerns the influence of organisational innovation on the relationship between *Learning capacity* and changes in working time required by the employer. The remaining mediations occur to the disadvantage of employees. A positive relationship that we did not observe in the overall population appears between the share of process innovative enterprises and involuntary part time work. It mediates partially both innovative inputs. The share of marketing innovative enterprises mediates positively the relationship between *Digital technologies adoption and use* and low working time autonomy. Finally, there is a partial mediation involving organisational innovation that weakens the protective relationship between the *Learning capacity of the organisation* and the possibility to take hours off for family or personal reasons.

In the North/East, it is the autonomy in the choice of time schedule that is not related with the shares of enterprises according to the innovation type. The full mediations that favour employees happen through the shares of product and of process innovative enterprises and they concern *Digital technologies adoption and use* only. Product innovation mediates positively its relationship with the possibility to take hours off for family or personal reasons and process innovation intervenes in its relationship with changes in working time required by the employer and involuntary part time. Note that this last relationship is opposite in the South/East. Another favourable partial mediation also found in the South/East relates the *Learning capacity* with changes in working time required by the employer through the share of organisational innovative enterprises. The mediations that are adverse for employees are concentrated on marketing innovation and concern both innovation inputs, with stronger effect for *Digital technologies* than for the *Learning capacity*. They lead to less possibilities to take hours off for family or personal reasons, to more frequent contacts on work matters during leisure time and to more involuntary part-time work.

Table 7: SEM regression by gender

	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
	LWTA: Time Schedule		LWTA: Hours off		Required change in WT		Contacted on work matter		Involuntary part-time work	
Digital technology adoption and use	0.047	-0.017	-0.001	-0.01	-0.010	-0.035	-0.023	-0.021	0.032	0.002
	(1.18)	(-0.41)	(-0.02)	(-0.31)	(-0.19)	(-0.85)	(-0.56)	(-0.63)	(1.50)	(0.25)
Learning capacity	**-0.910*** **	**-0.941*** **	**-0.708*** **	**-0.769*** **	**0.465*** **	**0.428*** **	**0.453*** **	**0.559*** **	**-0.100*** **	**-0.042** **
	(-13.25)	(-15.61)	(-13.36)	(-15.70)	(6.28)	(5.53)	(7.05)	(9.74)	(-3.97)	(-2.20)
Share of product innovative enterprises	-0.051	**-0.109*** **	-0.036	**-0.109*** **	0.033	0.048	-0.045	-0.026	-0.020	**-0.016** **
	(-1.45)	(-3.24)	(-1.30)	(-3.92)	(0.81)	(1.37)	(-1.25)	(-1.00)	(-1.02)	(-2.00)
Share of process innovative enterprises	0.019	0.011	0.03	0.013	**-0.074***	**-0.081** **	**-0.073***	**-0.051***	-0.002	-0.014
	(0.57)	(0.33)	(1.08)	(0.49)	(-1.67)	(-2.07)	(-1.89)	(-1.75)	(-0.08)	(-1.40)
Share of marketing innovative enterprises	0.040	**0.099*** **	**0.080*** **	**0.056** **	0.023	-0.011	**0.066***	**0.078*** **	0.007	**0.033*** **
	(1.33)	(3.07)	(2.97)	(2.21)	(0.64)	(-0.34)	(1.95)	(3.02)	(0.52)	(3.63)
Share of organisational innovative enterprises	**0.072***	0.048	**0.063** **	**0.066** **	**-0.071***	**-0.078** **	-0.013	**-0.060***	**0.034** **	**0.017** **
	(1.87)	(1.42)	(2.21)	(2.31)	(-1.80)	(-2.01)	(-0.39)	(-1.88)	(2.33)	(2.25)
Tertiary sectors (Ref: secondary sectors)	**0.033*** **	**-0.038*** **	**0.054*** **	-0.001	**0.038*** **	**0.065*** **	0.002	**0.026*** **	**0.028*** **	**0.017*** **
	(3.06)	(-4.01)	(5.57)	(-0.17)	(3.19)	(5.99)	(0.21)	(2.95)	(6.14)	(9.84)
Small enterprises (Ref :enterprise 50+)	-0.010	-0.008	0.005	0	0.006	**-0.020***	-0.006	-0.009	-0.008	**-0.010*** **
	(-1.02)	(-0.90)	(0.57)	(0.06)	(0.57)	(-1.86)	(-0.78)	(-1.08)	(-1.62)	(-4.60)
Region (Ref : Southern EU) Northern Europe	**-0.143*** **	**-0.131*** **	**-0.043*** **	**-0.069*** **	**0.044*** **	**0.027***	**0.058*** **	**0.050*** **	-0.007	-0.003
	(-11.09)	(-9.73)	(-3.85)	(-5.98)	(2.82)	(1.74)	(4.67)	(3.87)	(-1.14)	(-0.84)
Western Europe	**-0.142*** **	**-0.130*** **	**-0.018***	**-0.030*** **	**0.060*** **	**0.069*** **	0.004	0.016	**0.016** **	**0.009** **
	(-12.31)	(-10.93)	(-1.84)	(-2.95)	(4.13)	(5.17)	(0.34)	(1.50)	(2.51)	(2.41)
Central Europe	**-0.040*** **	**-0.032*** **	**0.034*** **	**0.025** **	-0.007	-0.009	0.015	0.016	**-0.035*** **	**-0.018*** **
	(-3.87)	(-2.75)	(3.07)	(2.13)	(-0.48)	(-0.60)	(1.52)	(1.40)	(-6.35)	(-5.99)
Constant	**1.305*** **	**1.387*** **	**0.819*** **	**0.943*** **	-0.035	0.069*	-0.036	**-0.058** **	**0.062*** **	**0.031*** **
	(41.19)	(44.72)	(33.11)	(38.32)	(-0.99)	(1.82)	(-1.23)	(-2.01)	(4.28)	(3.35)
Observations	657	661	657	661	657	661	657	661	657	661
R^2	0.79	0.80	0.75	0.77	0.69	0.69	0.67	0.70	0.69	0.68

	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
	LWTA: Time Schedule		LWTA: Hours off		Required change in WT		Contacted on work matter		Involuntary part-time work	
Digital technology adoption and use	0.047 (1.18)	-0.017 (-0.41)	-0.001 (-0.02)	-0.01 (-0.31)	-0.010 (-0.19)	-0.035 (-0.85)	-0.023 (-0.56)	-0.021 (-0.63)	0.032 (1.50)	0.002 (0.25)
Learning capacity	**-0.910***** (-13.25)	**-0.941***** (-15.61)	**-0.708***** (-13.36)	**-0.769***** (-15.70)	**0.465***** (6.28)	**0.428***** (5.53)	**0.453***** (7.05)	**0.559***** (9.74)	**-0.100***** (-3.97)	**-0.042**** (-2.20)
Share of product innovative enterprises	-0.051 (-1.45)	**-0.109***** (-3.24)	-0.036 (-1.30)	**-0.109***** (-3.92)	0.033 (0.81)	0.048 (1.37)	-0.045 (-1.25)	-0.026 (-1.00)	-0.020 (-1.02)	**-0.016**** (-2.00)
Share of process innovative enterprises	0.019 (0.57)	0.011 (0.33)	0.03 (1.08)	0.013 (0.49)	**-0.074*** (-1.67)	**-0.081**** (-2.07)	**-0.073*** (-1.89)	**-0.051*** (-1.75)	-0.002 (-0.08)	-0.014 (-1.40)
Share of marketing innovative enterprises	0.040 (1.33)	**0.099***** (3.07)	**0.080***** (2.97)	**0.056**** (2.21)	0.023 (0.64)	-0.011 (-0.34)	**0.066*** (1.95)	**0.078***** (3.02)	0.007 (0.52)	**0.033***** (3.63)
Share of organisational innovative enterprises	**0.072*** (1.87)	0.048 (1.42)	**0.063**** (2.21)	**0.066**** (2.31)	**-0.071*** (-1.80)	**-0.078**** (-2.01)	-0.013 (-0.39)	**-0.060*** (-1.88)	**0.034**** (2.33)	**0.017**** (2.25)
Tertiary sectors (Ref: secondary sectors)	**0.033***** (3.06)	**-0.038***** (-4.01)	**0.054***** (5.57)	-0.001 (-0.17)	**0.038***** (3.19)	**0.065***** (5.99)	0.002 (0.21)	**0.026***** (2.95)	**0.028***** (6.14)	**0.017***** (9.84)
Small enterprises (Ref :enterprise 50+)	-0.010 (-1.02)	-0.008 (-0.90)	0.005 (0.57)	0 (0.06)	0.006 (0.57)	**-0.020*** (-1.86)	-0.006 (-0.78)	-0.009 (-1.08)	-0.008 (-1.62)	**-0.010***** (-4.60)
Region (Ref : Southern EU) Northern Europe	**-0.143***** (-11.09)	**-0.131***** (-9.73)	**-0.043***** (-3.85)	**-0.069***** (-5.98)	**0.044***** (2.82)	**0.027*** (1.74)	**0.058***** (4.67)	**0.050***** (3.87)	-0.007 (-1.14)	-0.003 (-0.84)
Western Europe	**-0.142***** (-12.31)	**-0.130***** (-10.93)	**-0.018*** (-1.84)	**-0.030***** (-2.95)	**0.060***** (4.13)	**0.069***** (5.17)	0.004 (0.34)	0.016 (1.50)	**0.016**** (2.51)	**0.009**** (2.41)
Central Europe	**-0.040***** (-3.87)	**-0.032***** (-2.75)	**0.034***** (3.07)	**0.025**** (2.13)	-0.007 (-0.48)	-0.009 (-0.60)	0.015 (1.52)	0.016 (1.40)	**-0.035***** (-6.35)	**-0.018***** (-5.99)
Constant	**1.305***** (41.19)	**1.387***** (44.72)	**0.819***** (33.11)	**0.943***** (38.32)	-0.035 (-0.99)	0.069* (1.82)	-0.036 (-1.23)	**-0.058**** (-2.01)	**0.062***** (4.28)	**0.031***** (3.35)
Observations R^2	657 0.79	661 0.80	657 0.75	661 0.77	657 0.69	661 0.69	657 0.67	661 0.70	657 0.69	661 0.68

Table 8: SEM regression by geographical region

	LWTA: Time Schedule		LWTA: Hours off		Required change in WT		Contacted on work matter		Involuntary part-time work	
	North/West	South/East	North/West	South/East	North/West	South/East	North/West	South/East	North/West	South/East
Digital technology adoption and use	-0.05 (-1.03)	**0.087**** (2.11)	-0.007 (-0.20)	-0.044 (-0.98)	-0.024 (-0.49)	-0.055 (-1.13)	-0.015 (-0.32)	-0.010 (-0.28)	0.018 (0.96)	0.022 (1.60)
Learning capacity	**-1.099***** (-13.58)	**-0.522***** (-7.26)	**-0.797***** (-13.00)	**-0.732***** (-10.10)	**0.436***** (5.26)	**0.457***** (4.79)	**0.622***** (8.45)	**0.266***** (3.86)	-0.035 (-1.51)	**-0.058**** (-2.55)
Share of product innovative enterprises	**-0.087 *** (-1.82)	**-0.107***** (-3.18)	**-0.104***** (-3.01)	**-0.068**** (-2.00)	0.078 (1.61)	0.044 (1.17)	-0.022 (-0.60)	-0.033 (-1.18)	-0.005 (-0.32)	**-0.025*** (-1.79)
Share of process innovative enterprises	0.01 (-0.22)	0.008 (-0.22)	0.002 (0.07)	-0.004 (-0.10)	**-0.109**** (-2.24)	-0.044 (-1.04)	**-0.073*** (-1.82)	0.001 (0.05)	**-0.052***** (-3.31)	**0.032**** (1.96)
Share of marketing innovative enterprises	0.055 (-1.17)	**0.119***** (4.11)	**0.055**** (2.03)	**0.094***** (2.82)	0.045 (1.29)	-0.058 (-1.42)	**0.085**** (2.32)	-0.003 (-0.14)	**0.025**** (2.07)	0.023 (1.43)
Share of organisational innovative enterprises	0.034 (-0.76)	0.045 (1.39)	-0.013 (-0.41)	**0.129***** (3.48)	**-0.091**** (-2.19)	**-0.107***** (-2.84)	0.016 (0.36)	-0.046 (-1.53)	**0.025*** (1.68)	-0.002 (-0.22)
Tertiary sectors (Ref: secondary sectors)	0.004 (-0.26)	-**0.047***** (-4.85)	**0.027**** (2.54)	0.005 (0.39)	**0.048***** (3.76)	**0.040***** (2.74)	-0.011 (-0.85)	**0.033***** (3.82)	**0.032***** (8.91)	**0.016***** (5.31)
Small enterprises (Ref: enterprises 50+)	**-0.040***** (-3.17)	**0.024**** (2.56)	-0.003 (-0.32)	-0.000 (-0.02)	0.009 (0.71)	-0.029** (-2.24)	-0.001 (-0.13)	-0.011 (-1.38)	**-0.016***** (-3.33)	-0.004 (-1.21)
Constant	**1.369***** (-36.21)	**0.024**** (33.27)	**0.918***** (32.50)	**0.924***** (27.95)	**0.069*** (1.70)	0.058 (1.49)	**-0.082**** (-2.33)	**0.070**** (2.34)	**0.034***** (3.09)	0.018* (1.91)
Observations R^2	352 0.77	310 0.69	352 0.75	310 0.68	352 0.67	310 0.64	352 0.69	310 0.65	352 0.69	310 0.62

4. Innovation strategy, working time arrangement and work-life balance in French and British workplaces

We use linked employer employee data for France and Great Britain in 2011 to analyse the relationships between innovation, working time arrangements and work-life balance at the workplace level[2]. The data are cross-sectional and do not allow causal analysis to be carried out. However, the two datasets contain many individual and workplace-level variables (about the economic context, collective bargaining) that we use as controls in our analyses. In the first section, we present the two datasets, their comparability, the method as well as some descriptive statistics. The second section first presents the results about the relationship between innovation in the workplace and four flexible working-time practices (substantial part-time, short part-time, long hours, non-stable hours) and second, the consequences of these working time practices on workers' work-life balance.

4.1 Data and methodology

Data and comparability issues between the two datasets

The empirical strategy is based on two linked employer-employee databases (LEED), one French and one British. Data from both surveys were collected in 2011 and contain information on employment relations and on the dynamics of industrial relations between firm management, employee representative bodies, and employees. Previous comparative work using the two surveys has already been undertaken in the academic literature, including a comprehensive book on employment relations in France and Britain using 2011 data (Amossé et al., 2016).

The French survey is called REPONSE - 'Relations professionnelles et négociations d'entreprise', which means 'Industrial relations and collective bargaining' and has been carried out every six years on different samples since 1993 to 2017, providing cross-sectional datasets. The British survey is called WERS - Workplace Employment Relations Study - and has been undertaken 6 times (in 1980, 1984, 1990, 1998, 2004 and 2011). The British survey has unfortunately not been renewed after 2011. In order to have a relevant comparison, we will therefore use datasets from 2011 for both countries which corresponds to the post-Great Recession context[3].

These two databases offer many advantages to conduct comparative studies in the field of labour and employment. Even if they have not been explicitly harmonized, they provide comparable data, based on two surveys: one consisting in face to face interviews with managers responsible for employment relations in nationally representative samples of workplaces and another based on self-completion surveys conducted among randomly selected employees in the same workplaces. Amossé et al. (2016) have analysed the comparability of the questionnaires in 2011: despite differences in wording of the questions, management interviews provide

2 We also replicate the analysis for 2017 as an extension (the survey includes teleworking) and a robustness check, only for France as the British survey has unfortunately not been renewed.
3 We will present in appendix some complementary results for France in 2017 that is the last wave available and includes new variables especially on teleworking, a dimension of working time flexibility that has developed during the Covid pandemic and is likely to be particularly important in the future.

around 120 comparable data items. Employee questionnaires provide around 25 further comparable items.

Besides, the surveys also provide large samples for analysis (11,378 employees in 4,023 workplaces in REPONSE and 21,981 employees in 2,680 workplaces in WERS). Workplace samples do not offer full coverage of the economies, as both surveys exclude agriculture, forestry, fishing, and mining and quarrying and the smallest workplaces (less than 5 employees in WERS and less than 11 in REPONSE). Besides, public administration is excluded in REPONSE while it is not in WERS. In order to have more comparable results between France and Great Britain, we thus restrict the WERS sample to workplaces with less than 11 employees and also exclude public administration. These restrictions lead to a large drop in the number of employees in the WERS sample that becomes closer to that of REPONSE. In each country, samples of workplaces and employees are fully linkable. Our employee-level final datasets represent respectively French and British employees working in all workplaces that have 11 or more employees and are operating in Sections C-S of the Nace Rev. 2 Classification[4].

Considering the relationship between innovation, working time arrangements, and work life balance, the advantage of these surveys is that they contain precise information of working time arrangements (number of hours worked, non-stable hours) and work-life balance at the worker-level, but also include information at the establishment-level about the context of the workplace in terms of innovation and working-time management. Both surveys also include information about collective bargaining at the establishment level. All information about the workplace used in our analysis come from the employer questionnaire.

While REPONSE and WERS surveys focus on similar issues, questionnaires and variables are not built exactly the same way. We present here how we use initial variables and build new ones to ensure comparability of results between the two countries.

At the individual level, different variables have been created using the variable on the number of hours worked per week that is available in both surveys:

- 'Short part-time' for those working less than 24 hours a week,
- 'Substantial part-time for those working between 24 and 34 hours a week,
- 'Long hours' for those working more than 48 hours a week[5].

We also created a variable about non-stable working hours. In the French questionnaire, we use a categorical variable on the stability of working hours and create a dummy isolating the category "variable hours" (vs. same working hours every week or alternate hours - 2*8, 3*8, shift work). In the British survey, we use a slightly different variable that refers to the use of a flexi-time arrangement during the last 12 months. Flexi-time refers to a situation where an employee is not subject to a specific starting or finishing time but must work a defined number of hours per week or month. To come closer to this, 'Non-stable working hours' has been

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[4] Industry sectors T (activities of households as employers; undifferentiated goods and services producing activities of households for own use) and U (activities of extra-territorial organizations or bodies) are explicitly excluded from WERS. No mention of such an exclusion is made in REPONSE but they are likely to represent an insignificant share of employees, especially concerning households as employers given the restriction of the minimum number of employees in the workplace.
5 The 24-hour threshold was chosen in accordance with French legislation which, since 1 July 2014 and in the general case, defines the minimum duration of part-time work as 24 hours per week. The maximum threshold of 48 hours per week is the international standard adopted in the 1919 ILO Hours of Work Convention.

restricted in REPONSE 2011, so that it only takes into account hours which are variable from one week to another (excluding alternate hours from the dummy).

For work-life balance, we use scale variables that are relatively similar in the two surveys. In the REPONSE survey, employees are asked whether their work allow them to organise their private life satisfactorily (4-point scale: always, often, sometimes, never). In the WERS survey, employees are asked whether they often find it difficult to fulfil their commitments outside of work because of the amount of time spent on their job (from strongly agree to strongly disagree on a 5-point scale). From these two variables, we build an index of work-life balance (WLB) taking three different values: 0 (low WLB); 0.5 (intermediate WLB) or 1 (high WLB).

At the individual level, both surveys also contain comparable socio-demographic variables that we use as controls in our analyses, such as gender, age and occupation.

At the workplace-level, two different variables from REPONSE and WERS are used as proxies for innovative workplaces. Even though they do not come from exactly similar questions, they offer a rather good measurement of the general innovative and digital working environment. In the REPONSE survey, the technological and digital environment at the workplace is measured by a question about the firm's primary strategy, with innovation as one of the seven answers proposed. In WERS, the technological and digital environment at the workplace is measured by a question about the extent to which the workplace leads the way in terms of developing new products, services or techniques. On a five-point scale from "Very rarely leads the way" to "often leads the way", we consider innovative firms those whose employers answered "often leads the way".

We also look at the role of collective bargaining. In order to make the two variables the most comparable, we use: in REPONSE, a variable asking whether there has been any discussion or bargaining on the issues of wages, working time and training during the last three years (2008, 2009, 2010); in WERS, a variable asking whether management normally negotiate, consult, inform or not inform unions/non-union employee representatives about wages, working time and training. Even though more themes of discussion or bargaining are available in both surveys, we restricted the number of themes accounted for in our dummy variables, only keeping those available both in REPONSE and WERS (ie. wages, working time and training).

At the workplace-level, several additional variables are mobilised to control the companies' characteristics: size of workplace, sector, status (profit versus non-profit and type of ownership), and business activity situation (growing, stable, or declining).

Details about how comparable variables have been built from REPONSE and WERS are presented in table 9 below for main variables and for secondary in table A7 in appendix.

In terms of workplace size, the two samples are rather similar (table 10), including almost a half of workers employed in medium-sized workplaces, a third employed in small workplaces (less than 50 employees), and the rest employed in large workplaces (more than 500 employees, 17.3% in France and 19.6% in GB). The structure by economic sector differs, with a higher share of workers employed in the manufacturing sector in REPONSE (26.3% against 16.8% in WERS), while the share of workers in services (except retail) is higher in WERS (53% against 40.6% in France). That difference reflects the difference in industrial structure between France and Great Britain, which appears specialized in services, while France maintains a more substantial manufacturing sector (Amossé *et al.*, 2016).

Table 9. Construction and comparability of main variables used in REPONSE and WERS 2011

Final variables	REPONSE 2011	WERS 2011
Worker-level		
Substantial part-time *(between 24 and 34 hours)* **Short part-time** *(< 24 hours)* **Long-hours** *(> 48 hours)*	Question: On average, how many hours do you work each week? Variable: NBHSEM1_	Question: How many hours do you usually work in your job each week, including overtime or extra hours? (Exclude meal breaks and time taken to travel to work) Variable: qa4
Non-stable working hours Dummy 'Non-stable working hours' = 1 if …	Question: Are your hours … ? Variable: HORAIRE Modalities: 1. The same from one week to another 2. Alternating (2x8, 3x8, teams, shifts) **3. Variable from one week to another** 4. Don't know HORAIRE= *3*	Question: In the last 12 months, have you made use of flexi-time, and if not, was it available to you if you needed it? Variable: qb1a Modalities: **a. I have used this arrangement** b. Available to me but I do not use c. Not available to me d. Don't know qb1a = "a"
Work-life balance *Index of WLB created (3-level):* High level of WLB (1) Intermediate level of WLB (0.5) Low level of WLB (0)	Question: Does your work allow you to organise your private life satisfactorily? Variable: CONCIL Modalities: 1. Always 2. Often 3. Sometimes 4. Never CONCIL = *1* CONCIL = *2* CONCIL = *3 or 4*	Question: Do you agree or disagree with the following: I often find it difficult to fulfil my commitments outside of work because of the amount of time I spend on my job. Variable: qb2a Modalities: 1. Strongly agree 2. Agree 3. Neither agree nor disagree 4. Disagree 5. Strongly disagree qb2a = *4 or 5* qb2a = *3* qb2a = *1 or 2*
Occupation	Coded to PCS 2003 at four-digit level	Coded into SOC 2000 at four-digit level
Workplace-level		
Innovation strategy *Dummy: 'innovative workplace'=1 if…*	Question: In terms of the principal activity of your enterprise, can you indicate, from the list below, the main focus of your enterprise's competitive strategy? Variable: STRATEGIE Modalities: 1. Price **2. Innovation (strat_inno)** 3. Product quality 4. Service quality 5. Originality 6. Reputation, tradition, branding 7. Diversity of the offering 8. (Not applicable: no economic strategy, no competition) 9. (Do not answer) 10. (DK) STRATEGIE= 'Innovation (strat_inno)'	Question: Looking at the scale on this card, to what extent would you say this workplace leads the way in terms of developing new products, services or techniques? Variable: Kbainov Modalities: 1. Very rarely leads the way 2. 3. 4. **5. Often leads the way** Kbainov = 'Often leads the way'

Looking at workers' individual characteristics, the share of younger (less than 30) as well as older (over 50) workers appears higher in WERS than in REPONSE. In France, employment is concentrated in the middle of working life (between 30 and 49), with lower employment rates for youth and for seniors. The structure by occupation also differs, which reflects the differences in specialization mentioned earlier. Manual workers represent only 18% of workers in WERS, against 33.4% in REPONSE, whereas the share of professionals and managers as well as the share of clerical or sales workers is higher in WERS than in REPONSE.

Working-time arrangements in the two samples reflect important differences in national working time regime. Short part-time (less than 24 hours a week) appears far more frequent in WERS than in REPONSE (15.3% against 6.6%), and long hours (over 48 hours a week) are also more developed (12.6% against 8.3%). In France, working-time is indeed more regulated: according to a 2014 law, part-time should not be less than 24 hours, except in sectors where different agreements have been signed allowing for shorter part-time. There is no such limitation to part-time in the UK. In addition, France applies the European directive on working time that sets 48 hours as a maximum weekly working time, whereas the UK had opted out.

Table 10. Some characteristics of the sample

	REPONSE	WERS
Innovative workplace (% of employees)	10.3	19
Size of the workplace (% of employees)		
Less than 50 employees	35.3	31.4
Between 50 and 499 employees	47.4	49
More than 499 employees	17.3	19.6
Sectors (% of employees)		
Manufacturing	26.3	16.8
Construction	7.6	3.8
Transport	8.6	9.8
Retail and Wholesale	16.9	16.6
Other Services	40.6	53
Gender		
Female	41.3	44.5
Male	58.7	55.5
Age		
Between 15 and 29 years old	18	24.2
Between 30 and 49 years old	58.3	48.1
Older than 49	23.7	27.8
Occupation		
Professionals and managers	17.5	28.9
Technicians and associate professionals	22.4	13.6
Clerical or sales workers	26.8	39.5
Manual workers	33.4	18
Working time arrangements		
Substantial part-time (*usually work between 25 and 34 hours per week*)	8.7	7.6
Short part-time (*usually work less than 24 hours per week*)	6.6	15.3
Long hours (*usually work more than 48 hours per week*)	8.3	12.6
Non-stable working hours	33.1	23.4
N	**11,017**	**12,467**

Source: REPONSE and WERS databases (2011).
Reading note: all figures are shares of employees having a given characteristic. For workplace-level variables (innovation, size and sector), the figure is the share of employees who work in a workplace with this characteristic.

Finally, the share of employees working in an innovative workplace is higher in WERS than in REPONSE (19% against 10.3%), The wording of the questions may partly explain that difference, as the French question about "primary strategy" may be more restrictive than the British one asking if the workplace "often leads the way" in terms of new products, services etc.

According to descriptive statistics, substantial and short part-time as well as non-stable working hours are less developed in innovative workplaces, both in France and in the UK (table 11). Conversely, we find that the probability of working long hours is greater in innovative workplaces in both countries. However, there might be strong composition effects related to the specific characteristics of innovative workplaces and the next section investigates the relationship between innovation and working time arrangements, other things being equal.

Table 11. Innovation and working time arrangements

In %	Innovative workplaces		Other workplaces		Overall	
	REPONSE	WERS	REPONSE	WERS	REPONSE	WERS
Substantial part-time	6	6.5	9	7.9	8.7	7.6
Short part-time	3.4	14.7	7	15.4	6.6	15.3
Long hours	12.1	13.2	7.8	12.5	8.3	12.6
Non-stable working hours	28.7	21.6	33.6	23.9	33.1	23.4

Source: REPONSE and WERS databases (2011).

Looking at work-life balance variables in both surveys (table 12), it appears that French workers less frequently consider that they have a high level of work-life balance compared to British workers. This is partly related to the wording of the two questions in France and Great Britain and to the fact that the British question allows for a neutral answer "neither agree nor disagree" while the French question offers no middle answer (four-scale).

Table 12. Work-life balance: initial variables and common index

	REPONSE		WERS	
	Initial work-life balance variables			
	Does your work allow you to organise your private life satisfactorily?		I often find it difficult to fulfil my commitments outside of work because of the amount of time I spend on my job	
	Never	5.9	Strongly agree	8.4
	Sometimes	30.4	Agree	19.8
	Often	45.2	Neither agree nor dis.	24.4
	Always	18.5	Disagree	37.6
			Strongly disagree	9.8
	Common index…			
Low WLB	36.3		28.2	
Intermediate WLB	45.2		24.4	
High WLB	18.5		47.4	

Source: REPONSE and WERS databases (2011).

On the basis of the common index of work-life balance we built, we can see that about 36% of French employees have low levels of work-life balance which corresponds to those who answered that their work never or only sometimes allows them to organise their private life satisfactorily. Among British employees, only 28% agree or strongly agree that they often find it difficult to fulfil their commitments outside of work because of the amount of time they spend on their job. Conversely, 47% of British workers have high levels of work-life balance in the sense that they disagree or strongly disagree with that statement. In France, only 18,5% of employees answer that their work allow them to organise their private life satisfactorily.

Finally, the intermediate level of WLB concerns 24% of British employees but 45% of French. The different wording of the questions and the difference in scales may play a role here. However, we know from comparative surveys that French workers are on average less satisfied by their work and especially by their work-life balance than other European workers (see for instance Davoine, 2008, using ISSP), so this result on declared work-life balance may also reflect this more 'pessimistic' view from French workers.

Empirical Method

The empirical strategy is based on two different sets of models. The first one analyses the relationship between innovation (proxied with innovation as the firm's primary strategy) and four specific working-time arrangements: non-stable working hours, substantial part-time, short part-time and long hours. Empirically, it uses logit models with control variables at employee level (socio-demographic characteristics) and workplace level (including collective bargaining). The second set of models aims to identify the relationships between employees' perceived work-life balance and the different working time arrangements. In this second set, we carry out OLS regressions and include innovation strategy as well as employees' and workplaces' characteristics as independent variables. Workplace level and individual level controls are also included.

In all the models, the control variables at workplace level are the size, sector, the status of the firm (profit/non-profit) and of the workplace (headquarters/subsidiary), the level of activity over the past three years, and the existence of collective bargaining. The models are also controlled by employees' characteristics (gender, age, and occupation).

4.2 Results

Innovation and working time arrangements

In the first set of regressions, we test the hypothesis of a relationship between innovation and flexible working-time arrangements. More precisely, controlling for workplaces and employees' characteristics, we look at whether working in an innovative establishment has an impact on the probability of:

- working substantial part-time;
- working short part-time;
- working long hours;
- working non-stable (variable) hours.

According to the results presented in table 13, working in an innovative workplace significantly increases the probability to work long hours in both France and Great Britain. The effect on other working time practices in not significant. Therefore, despite differences in national working time regimes, the effects of innovation on working time practices appear quite similar.

Looking at control variables shows other similarities across the two countries. Being a woman increases the probability to work part-time (both substantial and short part-time) or to experience non-stable hours. Conversely, it decreases the probability to be concerned by long hours. Managers and professionals are more likely than manual workers to work long hours or non-stable hours in both countries, and less likely to work part-time (that effect is only significant in REPONSE, which may reflect the fact that the diffusion of part-time through all occupations is more important in Great Britain). Conversely, clerical and sales workers are less likely than manual workers to work long hours, but more often concerned by part-time (with the exception of short part-time in France) and non-stable hours than manual workers. Despite a few differences between the two countries, age effects generally show that being young (compared to the medium age group) tends to reduce the probability to work part-time or long hours. It also reduces the probability to declare non-stable working hours in GB, but increases it in France. Working in a large workplace tends to reduce short part-time in both France and GB, but it also reduces long hours in France, while it increases them in GB. The effect of service sector (retail and wholesale+ other services), compared to manufacturing, appears generally positive on all non-standard working time arrangements. The effects of workplace activity and status are mainly non-significant. Finally, the existence of collective bargaining at the workplace level tends to reduce short part-time as well as long hours in both countries. It also increases non-stable working hours in GB only. It is quite interesting to see that despite institutional differences, collective bargaining tends to reduce non-standard working hours in both countries. The difference for non-stable hours may be explained by the difference in their definition in the two surveys: in the British case, it focuses on workers'-oriented flexibility, and the results suggest a positive influence of collective bargaining on this type of flexibility.

Table 13. Working time arrangement regressions

	Substantial part-time		Short part-time		Long hours	
	REPONSE	*WERS*	*REPONSE*	*WERS*	*REPONSE*	*WERS*
Innovation strategy	-0.003	-0.028	-0.070	-0.026	0.213*	0.133*
	(0.140)	(0.088)	(0.189)	(0.068)	(0.114)	(0.080)
Female	1.499***	0.955***	1.332***	0.634***	-1.272***	-1.057***
	(0.096)	(0.087)	(0.113)	(0.062)	(0.105)	(0.077)
Occupation *(ref. Manual workers)*						
Professionals and managers	-0.397***	-0.112	-1.439***	-0.140	2.115***	0.537***
	(0.143)	(0.177)	(0.167)	(0.124)	(0.108)	(0.088)
Technicians and associate professionals	-0.194	0.246	-1.184***	0.288**	0.477***	-0.422***
	(0.123)	(0.187)	(0.138)	(0.132)	(0.119)	(0.125)
Clerical or sales workers	0.455***	0.966***	-0.925***	0.876***	-0.461***	-0.730***
	(0.113)	(0.161)	(0.126)	(0.115)	(0.171)	(0.103)
Age *(ref. Between 30 and 49 years old)*						
Between 15 and 29 years old	-0.415***	-0.513***	0.087	-0.165**	-0.177	-0.579***
	(0.106)	(0.095)	(0.126)	(0.066)	(0.122)	(0.094)
Older than 49	-0.186**	0.204***	0.690***	0.136**	-0.162*	-0.141**
	(0.087)	(0.076)	(0.095)	(0.063)	(0.091)	(0.070)
Size of the workplace *(ref. Less than 50 employees)*						
Between 50 and 499 employees	0.034	-0.032	-0.026	-0.277***	-0.090	0.221***
	(0.083)	(0.079)	(0.096)	(0.062)	(0.093)	(0.076)
More than 499 employees	0.294***	-0.209	-0.320**	-0.341***	-0.263**	0.210*
	(0.110)	(0.135)	(0.150)	(0.103)	(0.123)	(0.112)
Sector *(ref. Manufacturing)*						
Construction	-0.465*	-0.535	0.348	-0.028	0.261	0.479***
	(0.275)	(0.384)	(0.292)	(0.214)	(0.161)	(0.140)
Transport	0.481***	0.574***	1.060***	-0.245	1.675***	1.166***
	(0.161)	(0.184)	(0.208)	(0.158)	(0.121)	(0.115)
Retail and Wholesale	0.677***	0.749***	1.157***	1.128***	0.528***	0.020
	(0.133)	(0.164)	(0.200)	(0.117)	(0.136)	(0.133)
Other services	0.609***	0.710***	1.810***	0.599***	-0.071	0.227**
	(0.121)	(0.149)	(0.172)	(0.108)	(0.114)	(0.098)
Non-profit firm	0.420***	0.118	0.449***	0.258***	-0.143	-0.165*
	(0.099)	(0.086)	(0.112)	(0.071)	(0.181)	(0.093)
Establishment activity *(ref. Stable)*						
Growing	-0.158*	0.078	-0.098	0.035	0.108	-0.087
	(0.082)	(0.102)	(0.098)	(0.077)	(0.090)	(0.091)
Declining	-0.123	0.006	-0.078	-0.035	0.005	-0.293***
	(0.094)	(0.128)	(0.117)	(0.097)	(0.101)	(0.110)
Other		0.099		-0.055		-0.032
(turbulent)		(0.103)		(0.078)		(0.089)
Establishment status *(ref. Single-establishment)*						
Firm headquarters	-0.050	-0.127	-0.145	-0.189**	0.028	-0.245**
	(0.098)	(0.105)	(0.118)	(0.080)	(0.112)	(0.100)
Subsidiary establishment	-0.074		-0.122	-0.133**	-0.057	-0.115
	(0.089)	(0.085)	(0.105)	(0.066)	(0.098)	(0.079)
Collective bargaining	-0.076	-0.011	-0.360***	-0.128*	-0.208*	-0.592***
(same topics)	(0.117)	(0.085)	(0.128)	(0.067)	(0.126)	(0.082)
Intercept	-3.615***	-4.031***	-3.893***	-2.747***	-2.812***	-1.419***
	(0.177)	(0.201)	(0.217)	(0.141)	(0.169)	(0.125)
Number of Obs.	10867	11431	10867	11431	10867	11431
Pseudo R2	0.135	0.102	0.142	0.109	0.185	0.113
Log likelihood	-2833.146	-3112.377	-2074.221	-4608.299	-2475.414	-3566.04
Chi2	808.59	882.59	549.34	1434.88	705.92	1047.24

*Note: Standard errors in parentheses, level of significance * p<0.05, ** p<0.01, *** p<0.001. Logit regression analysis.*

Sources: REPONSE and WERS databases (2011).

Table 13. Working time arrangement regressions (continued)

	Non-stable working hours	
	REPONSE	*WERS*
Innovation strategy	-0.115 (0.075)	-0.009 (0.058)
Female	0.304*** (0.049)	0.127** (0.052)
Occupation *(ref. Manual workers)*		
Professionals and managers	0.469*** (0.068)	0.749*** (0.084)
Technicians and associate professionals	0.341*** (0.063)	0.757*** (0.095)
Clerical or sales workers	0.435*** (0.067)	0.213** (0.087)
Age *(ref. Between 30 and 49 years old)*		
Between 15 and 29 years old	0.188*** (0.059)	-0.142** (0.061)
Older than 49	-0.059 (0.051)	-0.145*** (0.054)
Size of the workplace *(ref. Less than 50 employees)*		
Between 50 and 499 employees	0.013 (0.050)	-0.052 (0.057)
More than 499 employees	-0.001 (0.067)	0.076 (0.080)
Sector *(ref. Manufacturing)*		
Construction	-0.283*** (0.104)	-0.388*** (0.147)
Transport	1.132*** (0.077)	-0.694*** (0.113)
Retail and Wholesale	0.842*** (0.074)	-0.453*** (0.104)
Other services	0.635*** (0.065)	0.195** (0.076)
Non-profit firm	0.106 (0.071)	0.292*** (0.061)
Establishment activity *(ref. Stable)*		
Growing	-0.050 (0.050)	-0.182*** (0.067)
Declining	-0.007 (0.055)	0.021 (0.080)
Other (turbulent)		-0.336*** (0.067)
Establishment status *(ref. Single-establishment)*		
Firm headquarters	-0.101* (0.061)	0.227*** (0.068)
Subsidiary establishment	0.059 (0.053)	0.047 (0.059)
Collective bargaining (same topics)	0.027 (0.072)	0.305*** (0.058)
Intercept	-1.400*** (0.096)	-1.753*** (0.105)
Number of Obs.	10867	11431
Pseudo R2	0.040	0.047
Log likelihood	-6594.389	-5800.101
Chi2	2277.78	1889.36

*Note: Standard errors in parentheses, level of significance * p<0.05, ** p<0.01, *** p<0.001. Logit regression analysis.*
Sources: REPONSE and WERS databases (2011).

We also run regressions for different subgroups of workers (by gender, skill level) to check if the effect of working in an innovative workplace on flexible working-time arrangements is the same across these groups (corresponding results are presented in table 14). The positive effect of innovation strategy on long hours that was found in the global sample is confirmed for women in Great Britain and for men in France. Models show some additional results when breaking down by subsamples, which appear country specific. The probability to work on a short part-time is lower for men in British innovative workplaces. Innovation strategy tends to reduce the probability of non-stable working hours for women in France. As far as skill level is concerned, it appears that working in innovative workplaces reduces non-stable hours and increases long hours for the low skilled in France.

To conclude, our first step shows limited effects of innovation strategy on working time arrangements in both France and Great Britain, which exemplify very different working-time regimes. The effects concentrate on long working hours, which would be increased in innovative environment.

Table 14. Effects of innovation on working time arrangements, by subsamples (regression coefficients)

Effects of innovation strategy on	Women		Men		Higher-skilled		Lower-skilled	
	REPONSE	*WERS*	*REPONSE*	*WERS*	*REPONSE*	*WERS*	*REPONSE*	*WERS*
Substantial part-time work	-0.041 (0.169)	-0.086 (0.102)	0.149 (0.254)	-0.130 (0.180)	0.173 (0.197)	-0.003 (0.167)	-0.204 (0.207)	-0.050 (0.104)
Short part-time	-0.186 (0.241)	0.046 (0.081)	0.012 (0.308)	-0.219* (0.127)	-0.036 (0.308)	-0.056 (0.122)	-0.063 (0.241)	-0.013 (0.083)
Long hours	-0.351 (0.300)	0.273* (0.145)	0.315** (0.125)	0.051 (0.096)	0.158 (0.124)	0.049 (0.104)	0.778*** (0.261)	0.110 (0.122)
Non-stable working hours	-0.328** (0.129)	-0.032 (0.080)	0.026 (0.093)	-0.001 (0.086)	-0.011 (0.093)	-0.031 (0.082)	-0.378*** (0.130)	0.038 (0.084)

*Note: Standard errors in parentheses, level of significance * p<0.05, ** p<0.01, *** p<0.001.*
The coefficients come from subsample logit regressions controlled by gender (when relevant), occupation (when relevant),
age, size of the workplace, sector, establishment's activity, regulation and status (not reported here).
Sources: REPONSE and WERS databases (2011).

Working time practices and work-life balance

In this second step of our empirical analysis, we analyse the relationships between flexible working time arrangements and employees' work-life balance. The general hypothesis in the literature is that non-standard hours tend to deteriorate work-life balance (Lott and Wöhrmann, 2022), while autonomy and sovereignty of employees over their actual working hours increase it (Lott, 2015) and may sometimes buffer the negative effect of non-standard hours (Fagan *et al.*, 2012). We also want to estimate a potential direct effect of innovation on work-life balance. To do so, we run two models, the first one including only the variable indicating if the employee works in an innovative workplace, the second one including the innovation variable and the four working time arrangements variables (substantial part-time, short part-time, long hours, non-stable hours).

According to our results (presented in table 15), innovation strategy in the workplace does not directly influence employees' work-life balance. Coefficients are not significant in both models, for the two countries. Working time arrangements have significant effects on work-life balance.

Table 15. Work-life balance, innovation and working time arrangements

Work-life balance	Model 1		Model 2	
	REPONSE	*WERS*	*REPONSE*	*WERS*
Substantial part-time work			0.035*** (0.012)	0.043*** (0.014)
Short part-time			0.101*** (0.015)	0.123*** (0.011)
Long hours			-0.175*** (0.013)	-0.269*** (0.013)
Non-stable working hours			-0.158*** (0.007)	0.023** (0.009)
Innovation strategy	0.002 (0.012)	-0.002 (0.010)	0.001 (0.011)	0.002 (0.010)
Collective bargaining	0.015 (0.012)	0.042*** (0.010)	0.016 (0.011)	0.028*** (0.010)
Female	0.073*** (0.008)	0.063*** (0.009)	0.040*** (0.008)	0.025*** (0.010)
Occupation *(ref. manual workers)*				
Professionals and managers	-0.037*** (0.011)	-0.072*** (0.013)	0.019* (0.011)	-0.053*** (0.013)
Technicians and associate professionals	0.016 (0.010)	0.024 (0.016)	0.037*** (0.010)	0.008 (0.015)
Clerical or sales workers	-0.007 (0.011)	0.078*** (0.013)	0.009 (0.010)	0.047*** (0.013)
Age *(ref. Between 30 and 49 years old)*				
Between 15 and 29 years old	-0.041*** (0.010)	0.017* (0.010)	-0.036*** (0.009)	0.005 (0.010)
Older than 49	0.042*** (0.008)	0.059*** (0.009)	0.035*** (0.008)	0.54*** (0.009)
Size *(ref. Less than 50)*				
Between 50 and 499 employees	-0.004 (0.008)	-0.014 (0.014)	-0.005 (0.008)	-0.004 (0.010)
More than 499 employees	-0.014 (0.011)	-0.010 (0.009)	-0.017 (0.010)	0.000 (0.014)
Sector *(ref. Manufacturing)*				
Construction	-0.016 (0.014)	-0.045** (0.022)	-0.022 (0.014)	-0.024 (0.021)
Transport	-0.081*** (0.013)	-0.161*** (0.017)	-0.022* (0.013)	-0.120*** (0.016)
Retail and wholesale	-0.050*** (0.012)	-0.032* (0.016)	-0.020* (0.012)	-0.045*** (0.015)
Other services	-0.030*** (0.010)	-0.061*** (0.013)	-0.19* (0.010)	-0.063*** (0.012)
Non-profit firm	0.013 (0.012)	-0.009 (0.011)	0.010 (0.012)	-0.019* (0.011)
Establishment activity *(ref. Stable)*				
Growing	0.019** (0.008)	-0.014 (0.012)	0.019** (0.008)	-0.017 (0.011)
Declining	-0.015* (0.009)	0.012 (0.014)	-0.014* (0.009)	0.003 (0.013)
Other (turbulent)		0.004 (0.011)		0.005 (0.011)
Establishment status *(ref. Single-establishment)*				
Firm headquarters	0.001 (0.010)	-0.018 (0.012)	-0.002 (0.010)	-0.022* (0.012)
Subsidiary establishment	-0.030*** (0.009)	-0.039*** (0.010)	-0.028*** (0.008)	-0.041*** (0.010)
Intercept	0.412*** (0.015)	0.602*** (0.017)	0.451*** (0.015)	0.639*** (0.017)
Number of Obs.	10812	11379	10812	11379
Adjusted R2	0.024	0.042	0.093	0.095
Log likelihood	-4066.454	-6076.3	-3667.223	-5748.067

*Note: Standard errors in parentheses, level of significance * p<0.05, ** p<0.01, *** p<0.001.*
OLS regression analysis.
Sources: REPONSE and WERS databases (2011).

In both countries, working part-time (substantial as well as short part-time) has a positive effect on work-life balance, whereas long hours have a negative effect. As far as non-stable hours are concerned, we find opposite effects: a positive one in Great Britain, and a negative one in France. That difference can be explained by the difference in the variables included in WERS and REPONSE. Non-stable hours indicate some worker-oriented flexibility in GB, which is not the case in France.

As in the first step, the results also show some common effects of individual or workplace characteristics in both countries. Women and older workers tend to declare a better work-life balance. Work-life balance appears lower in all sectors compared to manufacturing (with the exception of construction for which the coefficient is non-significant). Working in a subsidiary establishment (compared to a single establishment) also tends to reduce work-life balance. Some effects are also different in France and Great Britain. Younger workers tend to declare a lower work-life balance than the medium aged group in France, whereas the effect is non-significant in GB. Being a professional or a manager improves work-life balance in France (compared to manual workers), whereas it deteriorates it in GB. Finally, collective bargaining also has contrasted effects: it improves work-life balance in GB, whereas the effect is not significant in France.

Therefore, our results show some clear relationships between working-time arrangements and work-life balance. Part-time improves work-life balance and long hours deteriorate this outcome. Linking the two parts of our analysis, our results suggest that innovation induces a risk for work-life balance if it leads to longer hours (as suggested by the first regressions). This calls for specific attention in human resource management as well as in public policies, to avoid negative effects of innovation on employees' well-being.

Working time arrangements, innovation and work-life balance: an overview of most recent results for France (2017)

As mentioned in the methodological section, the last wave of WERS dates back to 2011 while in France REPONSE was carried out once again in 2017. We have used this last wave for France to analyse the relationship between innovation, working time arrangements and work-life balance, including some new information which was not available in 2011, especially about teleworking. Among flexible working arrangements, teleworking has significantly developed over the last decade (and even more since the Covid-19 pandemic) and is increasingly considered to be a work arrangement for the future. In REPONSE survey, employees also answer a question on the quality of information about working time at their workplace in 2016 which we include in our 2017 analysis. Since we do not need to restrain to comparable variables between France and Great-Britain for that year, we sometimes use variables with slightly different definitions than those presented in the methodological section but all details about the analysis for France in 2017 can be found in another working paper (Erhel *et al.*, 2021).

Results for France in 2017 confirm results from 2011 but also bring new insights especially on teleworking. The probability of working part-time is lower in establishments whose strategy mainly relies on innovation. The definition of part-time used here is slightly different (self-declared in that case and not distinguishing between short and substantial part-time). While no specific relationship appeared in 2011 between innovation and part-time work, this result echoes the higher frequency of long hours in innovative workplaces in 2011. Overall, in the

2010s, innovative workplaces thus seem to be characterized by limited part-time and/or more frequent long hours.

As far as non-stable working hours are concerned (including variable hours but also alternate hours here), no significant relationship appears when innovation is implemented as the primary strategy of the establishment, confirming for France the results in Great Britain in 2011.

Finally, the last flexible working-time arrangement we analyse in relation to the establishment's innovation strategy is teleworking[6]. Teleworking is not very widespread in 2017 (about 9% in REPONSE survey), but it is unevenly distributed across individual and establishment characteristics. Teleworking is more frequent for men, high-skilled workers and in large establishments and less frequent in manufacturing compared to all other industries. When we look at the relationship between innovation and teleworking, we find that workers more frequently work remotely when they work in an establishment whose primary strategy is innovation. This positive relationship holds for all subgroups of employees when we run separate regression by gender or skill level. Innovative workplaces are therefore more likely to develop teleworking compared to establishments whose primary strategy does not rely on innovation. This could be related both to the diffusion of ICT devices (more widespread in innovative companies) and to the organization of work (relying more on workers' autonomy) in these companies (Lorenz, 2015; Eurofound, 2017).

When it turns to the relationship between working time arrangements and work-life balance, we find similar results for part-time in France in 2017, compared to our results in 2011 for both France and Great-Britain. Working part-time increases work-life balance, in spite of slight differences in definitions used. Conversely, non-stable working hours and long hours reduce work-life balance, confirming for France our results from 2011. Our main new result is about the effect of teleworking. Teleworking is associated with a higher work-life balance in France in 2017. The variable used for teleworking is a dummy stating whether the worker work remotely or not, with no information on the intensity of teleworking (number of days of teleworking per week for instance). Before the Covid-19 pandemic, teleworking was far less developed and concentrated on white-collar workers in France. In that context, it seemed to have helped workers having a better work-life balance. As teleworking has widely developed over the last years, this can be seen as positive for work-life balance. However, this pre-Covid crisis result should be nuanced since more recent work in France (Beatriz *et al.*, 2021) shows that intense teleworking (more than 3 days a week) can impact different dimensions of job quality (longer hours, overlap on leisure time, reduced help from colleagues, lower health etc.) so that intense teleworking may also jeopardize work-life balance. Finally, the French questionnaire also includes a variable on the quality of information about working time at the workplace that has to be dropped for comparative purposes since it is not available in WERS survey. When we analyse its effect on work-life balance in REPONSE 2017, we can see that it has a strong positive effect, showing again how much workplace practices matter.

6 This paragraph on teleworking comes directly from the working paper by Erhel et al. (2021).

5. Conclusions

This report investigates with quantitative data the relationships between the technological transformation, working time quality and work-life balance through two different lenses. A first analysis is conducted EU-wide and at the a meso-level allowing to relate information from an employer level survey describing the technological transformation with information from a household survey capturing working time quality from the viewpoint of employees. A second analysis uses two comparable national linked employer-employee surveys at the workplace level, a French and a British one, to investigate the relationship between innovation strategy, working time arrangements and work-like balance. Both approaches have their limitations, but the methodology they deploy has the advantage of bringing together the responses of the best informants on technological transformation on the one hand, and on the quality of working time and work-life balance on the other.

The Beyond 4.0 integrated database ECS-LFS 2019 used in the first analysis combines at the sector-size-country level aggregated data from employer and employee level surveys. The 2019 European Company Survey (ECS) is used to describe the technological transformation and is integrated with the Labour Force Survey and its 2019 ad hoc module on "work organisation and working time arrangements". The approach used view the technological transformation as a relationship between three inputs - R&D activities, Digital technologies adoption and use and the Learning capacity of the organisation - and four types of innovation: two technological forms, product and process innovation and two non-technological ones, marketing and organisational innovations. By changing the way production takes place in time and space, the technological transformation then interacts with the quality of working time. This model implies that investments in *Digital technologies* and *Learning capacity* impact the quality of working time either directly or indirectly, through the mediation role of the different innovation types.

Estimating this model with Structural Equation Modelling, we find that investments into the Learning capacity of the organisation is a win-win strategy leading to more innovativeness and to a high road of better quality of working time. Indeed, a higher Learning capacity favours all forms of innovation. In terms of combination of innovations within firms, its drives non-technological innovation only and combinations of technological and non-technological innovation, but not technological innovation only. In higher *Learning capacity* sectors, employees are also less exposed to low working time autonomy and involuntary part-time. There are however three points of attention associated with the *Learning capacity of the organisation*. First, it induces more interferences of professional life with personal life, this negative effect being partially attenuated by process and organisational innovation. The higher working time flexibility at the initiative of employees granted in firms that invest into the *Learning capacity of their organisation* comes with a blurring of the frontier between personal and professional life. Second, firms' innovation strategies have a mediating role on the effect of the *Learning capacity* on the quality of working time. However, these effects are most of the time partial and they do not jeopardise the overall positive effect of the *Learning capacity*. Product innovation reduces low working time autonomy and involuntary part-time when marketing and organisational innovations augment them. Third, in most sectors, the level of the *Learning capacity of the organisation* has been stagnating over the last decade. Hence, barriers to its development need to be addressed.

Investments in digital technologies, meanwhile, have grown rapidly everywhere until 2019, with countries in southern, central and eastern Europe catching up with the rest of the EU. *Digital technology adoption and* use by sectors, as R&D and *Learning capacity*, favours innovativeness. Higher digital intensity drives all forms of innovation. In terms of combination of innovations within firms, higher investments in *Digital technology* favour technological innovation only and combined technological and non-technological innovation, but not non-technological innovation only. Contrary to investments in the *Learning capacity of the organisation* that generates direct impacts on working time quality, the impact *of Digital technology adoption* and use on working time quality is completely mediated by the innovation strategy of organisations. Product innovation mediates positively the relationship between *Digital technology adoption and use* and working time quality when the mediation effect of marketing innovation is opposite: it induces in digitally intensive sectors less working time autonomy and more work-related contacts during leisure time. Furthermore, if process innovation mediates positively the interferences of professional life with personal life by reducing them, organisational innovation mediates negatively the relationship between *Digital technology adoption and use* and working time autonomy by making it more difficult to take hours off for family or personal reasons.

The second empirical analysis is based on comparable surveys of employers and employees, a French one (REPONSE) and a British one (WERS) carried out in 2011, as well as similar data for France in 2017. These surveys provide information on labour and employment relations. The employer questionnaire examines the company's strategies, while the employees describe their work experience. The structure of the survey makes it possible to examine the relationships between innovation strategies, atypical working time arrangements and work-life balance at workplace level - controlling for many individual and workplace-level characteristics (about the economic context, collective bargaining) - and to make a comparison between the two sides of the Channel.

Two main results, which are common to the two countries, are obtained. First, working in an innovative workplace increases the probability to work long hours. In addition to the influence of some individual characteristics on atypical working time arrangements, the analysis also reveals the influence of some workplace-level features: in particular, collective bargaining at the workplace tends to reduce short part-time and long hours. Second, long hours deteriorate work-life balance, whereas part-time work improves it, suggesting that innovation can indirectly deteriorate work-life balance. As France and Great Britain exemplify very different working time regimes (flexible in GB, regulated in France, although firm-level flexibility has been increased), these relationships seem to exist beyond some institutional differences.

Analysis for 2017 in France brings an additional result about teleworking, which is increased in innovative workplaces, and tends to improve work-life balance. This type of innovation-related working time arrangement would therefore be more favourable for workers, although this effect has to be confirmed in the post-COVID period, as teleworking has been developed on a much larger scale and at a stronger intensity.

Overall, the analysis at the workplace level suggests that human resource management and public policies should pay attention to the potentially harmful effects of innovation on employees' well-being, and favour collective bargaining at the workplace that tends to mitigate these negative effects.

These workplace results do not fully corroborate the meso level analysis. A main reason is that although they both cover quality of working time and work-life balance issues, these two empirical analyses use different measures. In particular, they do not approach the technological transformation in a similar way. Hence, if we find a positive relationship between innovation strategy and long working hours the workplace level, we do not find any significant mediation role of innovation for this outcome at the meso level. However, in the North/West area, we find that the share of marketing innovative firms is associated with lower possibilities of taking hours off for family or personal reasons and more frequent work related contacts during leisure time, outcomes that are likely to impact negatively work-life balance issues. It is also interesting to note that the approach we have developed at a meso level could also be undertaken with linked employer/employee surveys at the workplace or company level. Such a survey covering simultaneous choices made by companies in the areas of technology and work organisation as well as employee level outcome would be the best data infrastructure to monitor the socioeconomic consequences of the technological transformation (Greenan et al., 2010).

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7. Appendixes

Table A1: Correlations between input, output and outcome variables

	R&D	Technology adoption and use	Learning capacity	Share of product innovative enterprises	Share of process innovative enterprises	Share of marketing innovative enterprises	Share of organisation innovative enterprises	Product and/or process innovative enterprises ONLY	Organisation and/or marketing innovative enterprises ONLY	Product and/or process AND organisation and/or marketing innovative enterprises	LWTA : Time schedule	LWTA : Hours off	Required change in working time	Contacted on work matter	Involuntary part-time	Long working hours 48+	Working from home
R&D	1.00																
Technology adoption and use	0.437*	1.00															
Learning capacity	0.238*	0.302*	1.00														
Product innovation	0.584*	0.463*	0.254*	1.00													
Process innovation	0.535*	0.493*	0.235*	0.711*	1.000												
Marketing innovation	0.320*	0.483*	0.275*	0.494*	0.443*	1.000											
Organisation innovation	0.059	0.111*	0.232*	0.155*	0.161*	0.116*	1.000										
Product and/or process innov enterprises ONLY	0.311*	0.0982*	0.0133	0.4107*	0.4529*	-0.2324*	-0.2119*	1.000									
Organisation and/or m innov enterprises ONLY	-0.226*	-0.094*	0.062	-0.330*	-0.389*	0.187*	0.394*	-0.330*	1.000								
Product and/or process AND organisation and/or marketing innov enterprises	0.461*	0.545*	0.311*	0.726*	0.721*	0.735*	0.344*	-0.093*	-0.253*	1.000							
LWTA : Time schedule	-0.176*	-0.156*	-0.646*	-0.134*	-0.102*	-0.105*	-0.070	-0.075	-0.012	-0.112*	1.000						
LWTA : Hours off	-0.209*	-0.206*	-0.623*	-0.193*	-0.157*	-0.107*	-0.046	-0.125*	0.070	-0.161*	0.811*	1.000					
Required change in working time	0.046	0.057	0.392*	0.038	-0.025	0.084*	-0.040	-0.005	0.021	0.032	-0.542*	-0.458*	1.000				
Contacted on work matter	0.006	0.100*	0.455*	0.016	-0.001	0.143*	0.061	-0.047	0.140*	0.054	-0.539*	-0.475*	0.444*	1.000			
Involuntary part-time	-0.034	0.130*	0.101*	-0.009	0.009	0.173*	0.053	-0.075	0.144*	0.064	-0.046	-0.051	0.110*	0.206*	1.000		
Long working hours 48+	-0.126*	-0.172*	0.056	-0.061	-0.050	-0.103*	-0.010	0.033	-0.008	-0.091*	-0.015	0.002	0.201*	0.018	-0.040	1.000	
Working from home	0.213*	0.135*	0.612*	0.154*	0.118*	0.133*	0.068	0.069	-0.011	0.139*	-0.799*	-0.697*	0.459*	0.547*	0.077*	-0.041	1.000

Table A2: Descriptive statistics on inputs, outputs and outcomes, by groups of sectors and geographical areas

	Total population		Sectors				Geographical areas			
			Secondary		Tertiary		North/West		South/East	
	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean	Obs
Inputs										
R&D	0,413 (0,26)	666	0,411 (0,28)	187	0,413 (0,25)	479	0,420 (0,26)	354	0,405 (0,26)	312
Digital technology adoption and use	0,452 (0,16)	666	0,418 (0,17)	187	**0,464*** (0,15)	479	**0,463*** (0,16)	354	0,438 (0,15)	312
Learning capacity	0,535 (0,08)	666	0,492 (0,08)	187	**0,552*** (0,08)	479	**0,565*** (0,09)	354	0,502 (0,07)	312
Outputs										
Share of product innovative enterprises	0,309 (0,20)	666	0,276 (0,21)	187	**0,322*** (0,20)	479	0,291 (0,19)	354	**0,328*** (0,21)	312
Share of process innovative enterprises	0,321 (0,20)	666	0,301 (0,19)	187	0,329 (0,20)	479	0,314 (0,19)	354	0,328 (0,20)	312
Share of marketing innovative enterprises	0,278 (0,19)	666	0,197 (0,16)	187	**0,309*** (0,19)	479	0,281 (0,18)	354	0,274 (0,19)	312
Share of organisation innovative enterprises	0,204 (0,15)	666	0,168 (0,14)	187	**0,218*** (0,15)	479	0,199 (0,14)	354	0,209 (0,16)	312
Outcomes										
LWTA : Time schedule	0,783 (0,15)	662	**0,831*** (0,14)	185	0,764 (0,15)	477	0,705 (0,15)	352	**0,871*** (0,09)	310
LWTA : Hours off	0,515 (0,12)	662	**0,534*** (0,11)	185	0,507 (0,12)	477	0,467 (0,11)	352	**0,569*** (0,11)	310
Required change in working time	0,286 (0,13)	662	0,239 (0,11)	185	**0,304*** (0,13)	477	**0,328*** (0,12)	352	0,239 (0,11)	310
Contacted on work matter	0,225 (0,10)	662	0,197 (0,10)	185	**0,236*** (0,10)	477	**0,251*** (0,11)	352	0,196 (0,07)	310
Involuntary part-time work	0,025 (0,04)	662	**0,046*** (0,01)	185	0,032 (0,04)	477	**0,033*** (0,04)	352	0,015 (0,03)	310
Long working hours 48+	0,048 (0,05)	662	0,045 (0,06)	185	0,048 (0,05)	477	0,045 (0,05)	352	0,051 (0,06)	310
Working from home	0,082 (0,09)	662	**0,045*** (0,06)	185	0,097 (0,10)	477	**0,123*** (0,11)	352	0,036 (0,05)	310

Table A3: WLS with robust standard errors and number of employees as weights

	LWTA : Time Schedule			LWTA : Hours off		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D	-0.0314	-0.0281*	-0.0236	-0.0465**	-0.0212*	-0.0103
	(-1.51)	(-1.95)	(-1.34)	(-2.48)	(-1.65)	(-0.70)
Learning capacity	-1.156***	-0.274***	-0.293***	-0.837***	-0.265***	-0.272***
	(-20.44)	(-4.73)	(-4.83)	(-18.88)	(-4.92)	(-4.92)
Digital technology adoption and use	0.065**	0.032	0.026	0.015	0.002	0.011
	(1.96)	(1.24)	(0.94)	(0.53)	(0.08)	(0.45)
LC x TAU	-0.596**	0.066	0.058	-0.236	0.212	0.238
	(-2.14)	(0.32)	(0.28)	(-1.09)	(1.21)	(1.34)
Female		0.083***	0.080***		0.004	0.003
		(3.41)	(3.25)		(0.19)	(0.11)
Age (Ref: 35 -54)						
15-34 years old		0.016	0.010		0.012	0.005
		(0.43)	(0.27)		(0.33)	(0.13)
55-64 years old		-0.065	-0.070		-0.077	-0.088
		(-1.07)	(-1.14)		(-1.27)	(-1.43)
Education		-0.419***	-0.412***		-0.289***	-0.284***
		(-14.28)	(-13.95)		(-11.26)	(-10.94)
Tertiary sectors (Ref: secondary)		-0.019**	-0.021**		0.028***	0.028***
		(-2.08)	(-2.28)		(3.42)	(3.28)
Small enterprises (Ref: enterprises 50+)		0.008	0.007		0.010*	0.009*
		(1.36)	(1.19)		(1.78)	(1.66)
Combination of innovations (Ref: non innovative enterprises)						
Product and/or process ONLY			-0.031			-0.031
			(-1.00)			(-1.21)
Organisational and/or marketing ONLY			0.020			0.024
			(0.67)			(0.87)
Product and/or process AND organisational and/or marketing			0.015			-0.017
			(0.55)			(-0.74)
Country dummies	NO	YES	YES	NO	YES	YES
Constant	1.389***	1.265***	1.169***	0.975***	0.719***	0.728***
	(50.68)	(32.95)	(22.37)	(39.67)	(18.25)	(17.65)
Observations	660	660	660	660	660	660
Adjusted R^2	0.424	0.780	0.780	0.386	0.726	0.727

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A4: WLS with robust standard errors and number of employees as weights

	Required change in working time			Contacted on work matter		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D	-0.0206	-0.0479***	-0.0300**	-0.0487***	-0.0221*	-0.0112
	(-1.06)	(-3.90)	(-2.11)	(-3.44)	(-1.81)	(-0.84)
Learning capacity	0.611***	0.0285	0.00900	0.562***	0.0444	0.0368
	(10.88)	(0.50)	(0.16)	(13.89)	(0.87)	(0.71)
Digital technology adoption and use	-0.0308	-0.0537**	-0.0400*	-0.00321	-0.0513**	-0.0411*
	(-0.94)	(-2.19)	(-1.65)	(-0.13)	(-2.38)	(-1.80)
LC x TAU	-0.543**	-0.365*	-0.357*	0.685***	0.0427	0.0830
	(-2.00)	(-1.77)	(-1.72)	(2.81)	(0.25)	(0.49)
Female		-0.0583**	-0.0576**		-0.0611***	-0.0637***
		(-2.19)	(-2.23)		(-2.81)	(-2.92)
Age (Ref: 35-54)						
15-34 years old		0.0492	0.0376		0.0940***	0.0861***
		(0.93)	(0.70)		(2.93)	(2.64)
55-64 years old		-0.155*	-0.177**		-0.0296	-0.0392
		(-1.78)	(-2.02)		(-0.60)	(-0.78)
Education		0.177***	0.186***		0.108***	0.114***
		(5.99)	(6.26)		(4.29)	(4.46)
Tertiary sectors (Ref: secondary)		0.0446***	0.0413***		0.0291***	0.0284***
		(5.97)	(5.49)		(4.13)	(4.01)
Small enterprises (Ref: enterprise 50+)		-0.0246***	-0.0247***		-0.0106**	-0.0115**
		(-4.53)	(-4.82)		(-2.20)	(-2.37)
Combination of innovations (Ref: non innovative enterprise)						
Product and/or process ONLY			-0.0649***			-0.0232
			(-2.91)			(-1.05)
Organisational and/or marketing ONLY			0.0118			0.0401
			(0.46)			(1.48)
Product and/or process AND organisational and/or marketing			-0.0244			-0.0190
			(-1.02)			(-0.91)
Country dummies	NO	YES	YES	NO	YES	YES
Constant	-0.0174	0.215***	0.238***	-0.0601***	0.0609*	0.0608*
	(-0.61)	(4.63)	(5.00)	(-2.88)	(1.77)	(1.79)
Observations	660	660	660	660	660	660
Adjusted R^2	0.159	0.850	0.959	0.251	0.653	0.657

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A5: WLS with robust standard errors and number of employees as weights

	Involuntary part-time work		
	(1)	(2)	(3)
R&D	**-0.024***** (-3.73)	-0.001 (-0.11)	-0.002 (-0.29)
Learning capacity	**0.050***** (3.21)	-0.031 (-1.28)	-0.038 (-1.53)
Digital technology adoption and use	**0.047***** (4.15)	0.003 (0.30)	0.000 (0.04)
LC x TAU	**-0.195**** (-2.46)	0.058 (0.80)	0.070 (0.92)
Female		**0.044***** (6.14)	**0.043***** (5.84)
Age (Ref: 35-54)			
15-34 years old		**0.075***** (5.62)	**0.074***** (5.63)
54-64 years old		**0.039**** (2.06)	0.042** (2.21)
Education		**-0.083***** (-7.55)	**-0.082***** (-7.50)
Tertiary sectors (Ref: secondary)		**0.020***** (6.60)	**0.020***** (6.44)
Small enterprises (Ref: enterprises 50+)		-0.004 (-1.46)	-0.004 (-1.64)
Combination of innovations (Ref: non innovative enterprises)			
Product and/or process ONLY			0.013 (1.20)
Organisational and/or marketing ONLY			**0.028**** (2.57)
Product and/or process AND organisational and/or marketing			0.010 (1.02)
Country dummies	NO	YES	YES
Constant	**-0.013*** (-1.69)	0.018 (1.34)	-0.008 (-0.55)
Observations	660	660	660
Adjusted R^2	0.062	0.454	0.459

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A6: WLS with robust standard errors and number of employees as weights

	Long working hours 48+			Working from home		
	(1)	(2)	(3)	(1)	(2)	(3)
R&D	**-0.016****	-0.011	-0.011	**0.044*****	**0.036*****	**0.039*****
	(-2.07)	(-1.53)	(-1.25)	(3.56)	(3.55)	(3.61)
Learning capacity	**0.083*****	-0.010	-0.012	**0.697*****	**0.126*****	**0.131*****
	(3.37)	(-0.34)	(-0.39)	(17.63)	(3.69)	(3.71)
Digital technology adoption and use	**-0.065*****	**-0.040*****	**-0.041*****	**-0.066*****	-0.003	0.002
	(-4.44)	(-2.91)	(-2.75)	(-3.37)	(-0.17)	(0.09)
LC x TAU	-0.133	0.020	0.017	**0.371***	-0.116	-0.108
	(-1.00)	(0.21)	(0.18)	(1.71)	(-0.73)	(-0.69)
Female		**-0.0693*****	**-0.0694*****		**-0.0487*****	**-0.0481*****
		(-6.42)	(-6.39)		(-3.46)	(-3.38)
Age (Ref: 35-54)						
15-34 years old		0.00340	0.00309		**-0.0698*****	**-0.0700*****
		(0.14)	(0.13)		(-2.93)	(-2.89)
54-64 years old		-0.0116	-0.0122		-0.0369	-0.0395
		(-0.29)	(-0.30)		(-1.09)	(-1.15)
Education		**0.0259***	**0.0264***		**0.250*****	**0.249*****
		(1.70)	(1.77)		(13.84)	(13.58)
Tertiary sectors (Ref: secondary)		**0.0174*****	**0.0172*****		**0.0247*****	**0.0250*****
		(3.35)	(3.22)		(4.25)	(4.25)
Small enterprises (Ref: enterprises 50+)		0.000790	0.000757		**0.00928****	**0.00952****
		(0.23)	(0.22)		(2.30)	(2.37)
Combination of innovations (Ref: non innovative enterprises)						
Product and/or process ONLY			-0.00460			-0.00313
			(-0.28)			(-0.16)
Organisational and/or marketing ONLY			-0.00209			-0.00365
			(-0.13)			(-0.13)
Product and/or process AND organisational and/or marketing			0.00139			-0.0114
			(0.11)			(-0.68)
Country dummies	NO	YES	YES	NO	YES	YES
Constant	0.0403***	0.106***	0.108***	-0.282***	-0.128***	-0.129***
	(2.99)	(4.31)	(4.31)	(-14.48)	(-4.78)	(-4.72)
Observations	660	660	660	660	660	660
Adjusted R^2	0.053	0.430	0.427	0.406	0.739	0.738

t statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Comparability of other workplace-level variables used as controls

Final variable	REPONSE 2011	WERS 2011
Collective bargaining	<u>Questions:</u> - *For working time and vocational training* During the last three years (2008, 2009, 2010) has there been any discussion or bargaining concerning the following issues? - *For wages* In terms of wages paid in 2010 in your enterprise, was there any discussion or bargaining with workforce representative or with employee?] <u>Modalities:</u> - *For working time and vocational training* **1. YES at establishment level only** **2. YES at enterprise level only** **3. YES at establishment and enterprise level** **4. YES** 5. NO 6. (DK) - *For wages* **1. YES** 2. NO 3. (DK)	<u>Questions:</u> Does management normally negotiate, consult, inform or not inform unions/non-union employee representatives about: rates of pay, hours of work, training of employees? <u>Modalities:</u> **1. Negotiates** **2. Consults** 3. Informs 4. None
Collective bargaining *Dummy: x=1 for …*	NEGSL10 ; TEMPSW_10 ; FORMPRO *x < 5*	epaya/epayb ; ehoursa/ehoursb ; etraina/etrainb *x < 3*
Non-profit firm	<u>Question:</u> Commercial code of the establishment (SIRENE 2010) <u>Modalities:</u> 1. Merchant **2. Non-profit, resources from private contributions (PR)** **3. Non-profit, resources from public contributions (PU)**	<u>Question:</u> How would you describe the formal status of this workplace (or the organisation of which it is a part)? <u>Modalities:</u> 1. Public Limited Company 2. Private limited company 3. Company limited guarantee 4. Partnership / Self-proprietorship **5. Trust / Charity** **6. Body established by Royal Charter** **7. Co-operative / Mutual / Friendly society** **8. Government-owned limited company / Nationalised industry / Trading public corporation**
Non-profit firm *Dummy: x=1 for …*	MARCHAND_ET *x = 'PR' & 'PU'*	astatus1 *x = 5 ; 6 ; 7 ; 8*
Establishment activity	<u>Question:</u> Over the last three years (2008, 2009, 2010), did the volume of business of your enterprise… <u>Modalities:</u> 1. Increase strongly 2. Increase 3. Remain stable 4. Decrease 5. Decrease strongly 6. (DK)	<u>Question:</u> Looking at this list, which of these statements best describes the current state of the market in which you operate [for your main product or service]? Modalities: 1. Growing 2. Mature 3. Declining 4. Turbulent
Establishment activity	CROISS	Kstamar An 'Other' category for x = 4 (turbulent market)

Table A7: Comparability of other workplace-level variables used as controls (continued)

Final variable	REPONSE 2011	WERS 2011
Establishment status	Questions: - *LIENS* Your enterprise or the enterprise to which your establishment belongs… - *siren_siege* Whether or not the establishment is a headquarters? - *MULTI* How many establishments does your enterprise possess in France, including the one we are in? Modalities: - *LIENS* 1. Operates as franchise 2. Is linked to a group of enterprises (GIE) or a business partnership arrangement, or belongs to a central purchasing unit 3. Belongs to a group 4. Is totally independent 5. (DK) - *siren_siege* 1. YES 2. NO - *MULTI* 1. Only one establishment (the one we are in) 2. Several establishments	Questions: - asingle Is this workplace one of a number of different workplaces in the UK belonging to the same organisation, a single independent establishment or the sole UK establishment of a foreign organisation? - *afranch* Is the workplace part of a franchise? - *aconhead* Is this workplace the controlling Head Office? Modalities: - *asingle* 1. One of a number of different workplaces in the UK belonging to the same organisation 2. Single independent establishment not belonging to another body 3. Sole UK establishment of a foreign organisation - *afranch* 1. YES 2. NO - *aconhead* 1. YES 2. NO
Establishment status *Categories:* *Subsidiary for …* *Single for …* *Headquarters for …*	 *LIENS < 4* *LIENS = 4* *siren_siege = 1 & MULTI = 2*	 *asingle = 1 ; 3 / afranch = 1* *asingle = 2* *aconhead = 1*

BEYOND 4.0

PART E - TASK 5.3
FROM PLATFORM WORK TO THE PLATFORMISATION OF WORK

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Deliverable type version: D5.1 – May 2023
Associated Work Package: WP5
Lead: CNAM-CEET
WP leader: Nathalie Greenan

beyond4.0.eu

European Commission

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 822296.

Document Summary

Document type:	*Deliverable D5.1 – Part E*
Title:	*From platform work to the platformisation of work: a European statistical analysis*
Author/s:	*Nathalie Greenan, Silvia Napolitano, E.K. Sarter, Chris Warhurst and Sally Wright*
Reviewer/s:	Sylvie Hamon-Cholet
Date:	15 *May 2023*
Document status:	*Final*

Abstract

With the advent of digital technologies, a new way of organising work through the distribution and allocation of labour using algorithms has emerged. Most policy and research attention on the use of these algorithms to coordinate productive activity is focused on platform work in the platform economy. This working paper investigates the possible extension of algorithmic management into non-platform companies. We measure this 'platformisation of work' as a form of work characterised by employees' lack of autonomy (time and procedural) which is reinforced by digital surveillance. We use data from the 2019 European Labour Force Survey ad hoc module on 'Flexibility of working time'. We then analyse how the platformisation of work relates to different strategies that organisations' have in terms of the adoption and the use of digital technologies, organisation of work and skills management. To this aim, we combine employee-level data from the LFS with employer-level data from the 2019 European Company Survey. This data covers a population of enterprises with 10 or more employees in a subset of sectors. Based on our analysis, the platformisation of work involves 11% of employees in the EU, suggesting that the policy interventions of the European Commission should also consider the use of algorithmic management amongst employees in non-platform companies in order to have greater impact for more workers. Results from our analysis show that in sectors where the learning capacity of the organisation is higher, employees are less exposed to the platformisation of work. By contrast, investments in digital technologies adoption and use are associated with an increase in the percentage of employees experiencing platformised forms work. Nonetheless, when investments in digital technologies and learning capacity are combined, this exposition is reduced.

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Executive summary

With the advent of digital technologies, new opportunities and challenges have opened up for businesses and workers. One key development is the emergence of a new way of organising work through the distribution and allocation of labour via digital platforms and the use of algorithms to coordinate productive activity. This development can potentially increase labour market participation for vulnerable or marginalised workers. It also represents a threat to standard employment. On the one hand, platform companies laud this development as offering platform workers opportunity to self-manage, choosing what work to do, when and how. On the other hand, these choices can be constrained by platform companies' use of algorithms to distribute and allocate tasks, meaning that control of work rests with the platform companies, not the workers. For many commentators, platform work represents the future of work. However, it is likely that this development currently affects only a very small percentage of EU workers – possibly less than 2% of them.

The focus on platform work is important but not sufficient. There is now a new awareness that the same digital technology and algorithmic management implemented by platform companies can be used to develop new ways of organising work within non-platform companies. We refer to this development as the 'platformisation of work' and we maintain that this focus has wider policy implications because it affects a much larger number of EU workers.

Existing research already points to the use of algorithms as a tool for organising work in a number of workplaces in hospitality, warehouses, retail, factories and healthcare. However, this existing research tends to focus on establishing its presence in workplaces rather than on analysing how the technological transformation affects employees in terms of reducing their autonomy and control over their work.

This paper aims to shed light on the potential extension of digitalisation of work and algorithmic management to non-platform companies. In particular, we focus on how the 'platformisation of work' relates to the different strategies organisations' have in terms of the adoption and the use of digital technologies, organisation of work and skills management.

To this aim, we use the available information from existing EU-wide surveys and build an EU-wide cross-country and cross-sector dataset that combines an employer survey (the 2019 European Company Survey- ECS) with an employee survey (the 2019 European Labour Force Survey - LFS - and its ad hoc module). The Beyond 4.0 integrated dataset ECS-LFS 2019 allows analysing a population of companies with 10 employees and more in a subset of sectors.

The main advantage of this dataset is that it fills a recognised statistical data gap in the EU: the lack of a EU-wide data source that links relevant information on employers and employees to better understand how companies' strategic choices regarding digital technologies and work organisation affect workers. The ECS 2019 gathers a comprehensive picture of the organisations' choices in terms of technology adoption and use; skills management and skills utilisation, organisational practices and management tools that support individual and organisational learning and innovation outputs. The LFS ad hoc module on 'Flexibility of working time' allows measuring the platformisation of work by drawing on variables capturing the lack of procedural and time autonomy reinforced by digital surveillance.

Nonetheless, obtaining a full picture of the phenomenon of platformisation through available statistical data is still challenging. The main issue is that the limited coverage does not allow to address a central feature of the digital transformation: the digitally operated networks, where the traditional employment relationship is challenged. Indeed, it is hardly possible to analyse how *Platformisation of work* concerns self-employed and employees in small companies.

Based on our analysis, *Platformisation of work* affects 11% of employees in the EU. Our results show that investments in digital technologies are associated with an increase in the percentage of employees with platformised work. By contrast, in sectors where the *learning capacity of the organisation* is higher, this form of work is less prevalent. Nonetheless, when investments in digital technologies, their adoption and use and organisational and learning capacity are combined the incidence of *Platformisation of work* is reduced.

While we need to qualify these findings by recognising the data deficit, they do however highlight the extension of algorithmic management into non-platform companies. *Platformisation of work* affects many more workers, as employees in these companies, than workers in the platform economy. These findings suggest that the European Commission should also consider the use of algorithmic management amongst employees in companies in the non-platform economy. Policy intervention here might both be more needed and have greater impact for more workers. Such policy would also align with and further the specifications to improve job quality in the EU through the European Pillar of Social Rights. It would also dovetail with the European Commission's new Digital Services Act, matching strong consumer protection with good worker protection underpinned by the same type of transparency and accountability framework. Such protections may also be helpful for companies as *Platformisation of work* might be dysfunctional for employers. While companies can achieve short-term gains in efficiency by using algorithmic management, these strategies favour exploitation rather than exploration and can limit the potential for innovation. Furthermore, they risk eroding important line management relationships and dehumanising workers. As shown by our analysis, the promotion of investments in the *Learning capacity* of the organisation would be a way to counteract *Platformisation of work*.

It would also support new European Commission's Industry 5.0 initiatives to promote greater productivity gains through a more human-centric approach to the use of digital technology. The European Commission has a role in shaping the future of work in the putative Digital Revolution. Addressing the *Platformisation work*, not just platform work, has to become a policy priority with the aim of freeing Europe from the perceived constraints imposed by technology on work organisation and instead choosing what constraints to impose upon the use of technology in work.

1 Introduction: digital technology and the future of work

With the advent of digital technologies, new opportunities and challenges have opened up for businesses and workers. One key development is the emergence of a new way of organising work by distributing and allocating it via digital platforms. This development marks a shift towards the use of digital networks (platforms) by some new companies and the use of algorithms to co-ordinate productive activity involving the matching of the demand for and supply of resources. Although intermediaries that mediate the supply and demand for labour have existed for centuries, for many commentators, platform work with its digitally matched demand for and supply of labour represents the future of work (Rahman and Thelen, 2019). Opinions, however, are divided as to whether it is a beneficial or detrimental development for workers, and, as we outline below, a large body of research now explores this issue (Mathieu and Warhurst, 2020).

Given that the levering of this digital technology is new – and some would go so far as to call it a 4th Industrial Revolution (Schwab, 2016) – one of the challenges is measuring its extent and hence impact. In broad terms, platforms can be understood as digital intermediaries that enable interactions between at least two kinds of users: services and/or goods providers and consumers of these services and goods (for example, ILO 2022b; Kovalainen et al., 2020). This broad understanding includes a common distinction between platform companies that facilitate the selling or renting of goods and those that centre on the provision of labour services (Forde et al., 2017). With respect to the latter, the companies operating these platforms offer themselves as brokers between customers who demand labour and workers who might provide it. They are adamant that they are not employers of these workers. In Beyond 4.0, we refer to this development as the 'digitalisation of work' (Mathieu and Warhurst, 2020), though it is expressed through a variety of terms (ILO, 2022b), such as 'platform work', 'gig work' and 'Uberisation'.

Typically, policy and research concerned with the digitalisation of work focus on these labour services platforms as they operate in the labour market. This research is important. However, it is also limited. There is now growing awareness that the same digital technology can be used to develop new ways of organising work within non-platform companies (Fernández-Macías et al., 2023). In other words, the digitalisation of work might not be confined to platform companies but extend beyond these particular companies and their so-called 'gig workers', affecting non-platform companies that have employees (Eurofound, 2021b).

This working paper analyses this extension of the digitally supported platform approach to non-platform companies. The use of algorithmic management by both types of companies - platform and non-platform - raises specific questions about the employment status of their workers and suggests points of convergence around work control. It is important for research to recognise this potential dual use because the extension of algorithmic management to non-platform companies means that it is likely to impact many more workers and thus have broader policy implications.

The next section focuses on platform work. It explains this type of work as fragmented into tasks and the algorithmic management used to organise and control this work and its tasks. It also outlines how this control has given rise to policy concerns and responses about the employment status of platform workers. The following section then shifts the focus to the *platformisation of work* and how algorithms might be used to control employees within non-platform companies. The subsequent section outlines the data, methods and results of our original analysis of the Platformisation of work in Europe. Drawing on EU-wide statistical data, it develops a composite indicator for the *Platformisation of work* and applies it to investigate developments within EU enterprises. After a short summary of the findings on the platformisation of work, the concluding section discusses the workplace implications of our findings and relates them to current EU policy development.

2 Platform work: who's in control?

Platform work is 'work mediated by an app or a website that matches demand for labour to the provision of products or services in return for money' (ILO, 2022a: vii; see also Eurofound, 2018; Pesole et al., 2018). Platforms that broker labour services use algorithms to match the demand and supply of paid labour. This platform work can be distinguished into online web-based work, which operates entirely online and can draw on a global workforce (crowdworking), and location-based work, which requires the worker to be in a specified location. In both cases, however, workers are typically offered not a job but pieces of work (i.e., tasks). With this 'taskification' of work, payment can be set at a fixed price or be based on negotiation between workers and users (Forde et al., 2017; Mathieu and Warhurst, 2020).

Tasks performed by platform workers can be mental and manual. The taskification of work is not new, it stretches back to at least Charles Babbage and Adam Smith in the 1st Industrial Revolution and was made acutely manifest in the marriage of Taylor's scientific management and Ford's use of the moving assembly line in the early twentieth century (Thompson and McHugh, 2009). In addition, intermediaries that mediate and match labour market supply and demand are also not new, it occurred at medieval fairs across Europe for example. Temporary work agencies in the second half of the twentieth century similarly matched supply and demand for office workers (see, ILO, 2018; Urzì Brancati et al., 2020). What is new is the use of algorithms to optimise the matching of the demand for and the supply of labour, overcoming the issue of spatiality where necessary and often in real time. That is, algorithms can meet supply and demand where it is needed and at the point of need.

Put succinctly, this digitalisation of work results in:

- Work migrating to platforms, with platform companies presenting themselves as brokers of work, not employers of those who carry out the work.
- Provision by workers of tasks that might once have been bundled together to comprise a job with an employment contract.
- Work that is contingent, occurring 'on-demand' as and when needed, and paid by task.
- All this productive activity is managed through algorithms controlled by the platform companies.

As such, platform work is an expression of non-standard employment and part of an existing trend of dismantling the standard employment relationship that provides workers with permanent and full-time employment with a single employer (Bosch, 2004).

Platform work creates labour market opportunities. It offers workers a high degree of autonomy in terms of the choice of tasks, as well as the location and time of work. By enabling workers to choose where and when to work, it can provide flexible work opportunities as well as an entry point into the labour market for disadvantaged or marginalised workers who have difficulty partaking in standard employment (De Stefano et al., 2021; Eurofound, 2021a, 2021b; Hadwiger, 2022; Pesole et al., 2018; Urzì Brancati et al., 2020). As a result, according to Urzì Brancati et al. (2020: 7), platforms 'can increase participation in the labour market through better matching procedures'.

At the same time, these opportunities can be hard to realise. Access to decent work is sometimes difficult as the lack of regulation can result in poor working conditions. Issues include but are not limited to insecure income, unpaid working time and atypical working hours. With payment only per task, it is not uncommon for platform workers to be engaged in more than one task and to work across a number of platforms to realise a decent standard of living. Moreover, there is often an absence of dispute resolution mechanisms, with challenges to collective organisation and bargaining (De Stefano et al., 2021; Pesole et al., 2018; Eurofound, 2021b; Hadwiger, 2022; ILO, 2018; Urzì Brancati et al., 2020; Wood et al., 2019; Flanagan, 2019; van Doorn, 2022).

Importantly, those workers undertaking tasks are not employees of the platforms (ILO, 2018), which contend that they are not employers and their workers not employees but instead self-employed; they are presented as entrepreneurs, people who want to be and are their own boss, choosing what work to do, when and how. These workers are said to be liberated from the pressures and constraints of the employment relationship, self-managing their working lives.

The issue, however, is the reality of this worker autonomy. While platform workers are free to make choices, in practice, these choices are constrained by platform company requirements (Eurofound, 2021b; Waldkirch et al., 2021; Wood et al., 2019). Whilst algorithms distribute and allocate tasks, it is the platform companies, not the workers, who control the algorithms. In some cases, workers are automatically allocated tasks with only limited opportunities to refuse them, while in other cases workers are free to accept or refuse tasks offered to them but with a short timeframe for decisions and on the basis of limited information (Wood, 2021). Algorithms also evaluate workers' performance, including the rate to which workers accept the tasks as well as customer or client rankings and reviews of workers. Non-compliance with requests to supply labour or failure to follow prescribed procedures can result in workers' accounts being temporarily or permanently suspended by the platform company (Flanagan, 2019; Rosenblat and Stark, 2016; van Doorn, 2020; Wood, 2021; Wood et al., 2019). In practice, as Kovalainen et al. (2020: 46) argue, 'algorithms represent a new control mechanism' that, coupled with surveillance tools, affects the scope of workers' discretion and control over their work. Likewise, Forde et al. (2017) found that while workers have discretion over the intensity of work, they have only limited autonomy in fulfilling this work. While flexibility to choose work and working times is valued by workers, it is a 'freedom … under algorithmic control' (Griesbach et al., 2019: 13).

The issue of control shapes debates about the legal status of platform workers. A key distinguishing feature between the employed and the self-employed lies in worker control and self-direction (Countouris, 2019; Forde et al., 2017: 31; Kovalainen et al., 2020; Urzì Brancati et al., 2020). As a general rule, having the freedom to determine when, how and where to undertake work for customers and clients defines self-employed workers. Employees do not enjoy the same freedom; their work is under the direction of an employer, who also evaluates, disciplines and rewards their labour. Employees in turn enjoy rights and protections that self-employed do not, for instance a minimum wage, maximum working hours, protections against unfair dismissal and social security benefits linked to their employment status. The legal status of platform workers – whether they are self-employed, employees or a third category of worker – is therefore of crucial importance to workers, platform companies and governments.

Given the issue and the importance of control, the claim made by most platforms that they are mere brokers and that their workers are self-employed has increasingly been challenged, including in courts (De Stefano et al., 2021: 34-35; Eurofound, 2021b: 14; Thelen, 2018; Urzì Brancati et al., 2020: 5). These courts have reached different conclusions regarding the status of platform workers. Some courts have ruled that the relationship between a platform company and platform worker constitutes an employment relationship, others have concluded that platform workers are self-employed. Different courts have even ruled different worker statuses in cases involving the same platform company (De Stefano et al., 2021; Urzì Brancati et al., 2020; Forde et al., 2017).

To address this problem, the European Commission has decided to act. In 2021, it issued its Communication *Better working conditions for a stronger social Europe*, which stated that:

> *New ways of organising work, such as platform work, make it more complex to correctly classify people as workers or self-employed. This leads to situations where some people are unfairly deprived of access to the rights and protections associated with the worker status* (European Commission, 2021a: 1).

The Communication specifically pointed to algorithmic management, highlighting that it 'deprives [platform workers] of the autonomy enjoyed by a genuine self-employed person' (p.3) and that it can contribute to platform workers being misclassified as self-employed. It called for 'an immediate and dedicated policy response' (p.3). In the same year, the European Commission issued a Proposal for a Directive that requires Member States to adopt measures that enable the classification of platform workers as employees or self-employed in which there is 'the legal presumption that an employment relationship exists between the digital labour platform and a person performing platform work, if the digital labour platform controls certain elements of the performance of work' (European Commission, 2021b: 15).

This initiative is important, not least for platform workers and platform companies. Based on the issue of control, it promises to provide clarity on employment status and thereby the rights of workers and the responsibilities of companies where currently ambiguity reigns.

However, the degree of coverage provided by the Directive may be low. The problem is that the extent of platform working is unknown, in large part because of definition and measurement issues (Piasna et al., 2022). Because of the propriety rights of platform companies over their data, only the companies themselves know its extent (Pesole et al., 2018). In the absence of data from companies, different studies use different definitions of who counts as a platform worker (Fernández-Macías et al., 2023). Depending on the definition, assessments of the scope and characteristics of platform work differ considerably. Reflecting differences in engagement, Huws et al. (2019) estimated that about 4.7% of adults in the UK and 28.5% in Croatia carried out 'some form of platform work at least weekly' (p.1). Other studies find that while nearly one third of respondents had engaged in online work more broadly at some time, only 17% of them had done so in the year preceding the survey (Piasna et al., 2022), revealing that most platform work is occasional. Focusing on platform work as a specific sub-set of internet work reduces the extent to 4.3% of respondents (Piasna et al., 2022). Urzì Brancati et al. (2020) distinguish between sporadic, marginal, secondary and main platform workers and found that only 1.4% of respondents in their study could be classified as main platform workers. While Fernandez-Macias et al. (2023) found that approximately 1% to 2% of the working age population in Spain and Germany do platform work for digital labour platforms (DLPs) as their main job.

While for some, platform work provides the sole income, for others it provides only supplementary income. Indeed, platform working often coincides with other forms of employment, indicating that workers combine platform work with other (regular) types of employment (Forde et al., 2017; Urzì Brancati et al., 2020; ILO, 2022b, 2021). Despite Rahman and Thelen (2019) opining that platform work represents the future of work, it could, hence, be that less than 2% of workers are solely platform workers, with not many more regularly undertaking some form of platform work in Europe. In terms of coverage, of far greater importance might be the extension of algorithmic management to employees within non-platform companies. It is to this possibility that we now turn.

3 The platformisation of work: algorithmic control of employees in non-platform companies

While platform work currently receives a huge amount of research and policy attention, it should be remembered that its emergence is only one part of a much wider 'Digital Revolution' with technological change expected throughout the European economy (Eurofound 2018). As Poell et al. (2019: 5-6) highlight, digitalisation is proliferating, with a 'penetration of the infrastructures, economic processes, and governmental frameworks of platforms in different economic sectors and spheres of life'. Digitalisation therefore will impact work and its organisation more broadly, reaching into non-platform companies (Chicchi, 2020; Gonzalez Vazquez et al., 2019; Kovalainen et al., 2020; Richardson, 2021).

In platform work, algorithmic management is used to direct, evaluate, discipline and reward workers. The same form of management, we argue, can be extended in the organisation of work in non-platform companies. Indeed, existing research points to the use of algorithms as a tool for organising work in such diverse settings as hospitality, warehouses, retail, factories, marketing companies and healthcare services and as a means for evaluating workers, for example in call centres, retail, delivery and consultancy and banking. Furthermore, it has been shown that algorithmic tools are also used to inform disciplinary action against workers, for instance in warehouses (for an overview over the relevant literature see Wood, 2021).

Whilst the use of algorithmic management to control work and workers is a key feature of platform work, control of any productive activity is important.[1] For Braverman (1974), scientific management – or Taylorism as it is sometimes called – is the expression of this control within capitalism. Being an engineer, Taylor sought to apply the rationality that underpins engineering to productive activity within companies. Three points about scientific management are relevant to our analysis. First, it involved the development of a science for each element of work, derived through observation and measurement of workers at perceived optimal productivity. Second, it aimed to provide detailed instructions about how work should be carried out based on the best or most efficient way of working gleaned from the scientific study. Third, it created a dual division of labour: first, between managers and workers, leading to a separation of conception/planning and execution/doing; and, second, between workers themselves with the fragmentation of work into tasks, with individual workers allocated specific tasks as part of their job description. Within this last point both vertical and horizontal technical divisions of labour occurred within companies (Taylor, 1947).

Albeit intended to improve management as a process, Taylorism created and legitimised ‘managers’ with a function to organise and control the labour process and, with it, workers. These managers were provided with a body of knowledge about how work should be performed; this knowledge was legitimatised through the evoking of rational authority stemming from the application of scientific principles. While, to his dissatisfaction, scientific management as Taylor envisaged it was never fully implemented (Thompson and McHugh, 2009), some of its principles were applied and continue today in both the manufacturing and services industries (see, respectively, Williams et al., 1994 and Gould, 2010).

Scientific management as a form of control is linked to technology use. Control of the labour process is central to organisations but the specific forms of control can vary, for example between personal, technical and bureaucratic control (for an overview, see Thompson and McHugh, 2009). In this respect, there is a long history of technology being used to organise and control work and workers, from the emergence of power-driven machinery in the mills and factories of the 1st Industrial Revolution to the use of keyboard surveillance software

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[1] Within this productivity activity, the labour process is a core function of all organisations. The labour process is ‘the application of labour to the means of production (materials and whatever technological devices are available) to produce use values’ (Ramsey, 1985: 58). It is sometimes loosely referred to as ‘work organisation’. Within capitalism the use values created in the labour process attain exchange value through the market. Importantly, it is through the labour process that value is created and appropriated, thereafter distributed according to the form of ownership of the firm (Nichols, 1980). Control of the labour process is therefore a practical and political act. Within capitalism, employers exercise a managerial prerogative (however moderated) to direct, evaluate, discipline and reward labour within the labour process. With control as the means and success in the market as the measure, competitive pressures impel managers as employers in loco to try to continually transform productive activity to generate and secure surplus (Thompson, 1989).

among call centre workers in the late twentieth century. Interestingly, Beirne at al. (1998) have shown how the same process of control through technology has been allied to the 'thinking work' of software engineers in the late twentieth century by using their own software against them. Similarly, through new software applications, a new Digital Taylorism attempts to capture and routinise the know-how of technical and professional employees. It involves 'the extraction, codification and digitalisation of knowledge into software prescripts and templates' (Lauder et al., 2017: 414).

While control through algorithmic management is at the core of the classification of platform workers' status, the use of algorithmic management as a form of technical control is not necessarily limited to platform work. Algorithmic control may thus be an increasingly important feature of work in non-platform companies (Ball, 2021; Eurofound, 2021b; Fernández-Macías et al., 2023). Algorithmic management can be used to direct, monitor and evaluate employees (Ball, 2021; Eurofound, 2021b; Huws et al., 2019). Moreover, Kellogg et al. (2020) suggest that within and beyond platform work, algorithmic management has the potential to be more insidious and more exacting than previous forms of control, technical or otherwise. It could hence, they say, be 'more encompassing, instantaneous, interactive, and opaque than previous technological systems' (p.366).

We contend that this extension of algorithmic management to employees in non-platform companies represents the 'platformisation of work', which we define as a form of work characterised by employees' lack of autonomy (time and procedural) reinforced by surveillance through digitalised systems.

Nevertheless, whilst algorithmic management offers the potential to be transferred to non-platform-based employment, representative research at a large scale, which examines this development, is still missing (Wood, 2021). Existing research seems to focus on establishing the presence of algorithmic management in workplaces rather than systemically exploring its impact on employees. Part of the reason, as Ashton et al. (2017) suggest, is because Digital Taylorism is a process that is still in its early stages. Little research exists that examines its impact on employees and, as Lauder et al. (2017) illustrate, the research that does exist focuses on technical and professional employees. We contend that that the platformisation of work is likely to be applied more broadly than to technical and professional employees only.

Because the platformisation of work has the potential to reorganize work and increase control over work in a larger portion of the workforce than those involved in platform work, it is crucial to explore it. However, a serious data deficit exists in the EU when it comes to capturing the extent and nature of platform work, the platformisation of work and indeed the impact of digitalisation on work and employment more generally (Greenan and Napolitano, 2022). The need to improve data on platform work has been recognised and addressed through the JRC Algorithmic Management and Platform Work (AMPWork) pilot survey[2] (Fernández-Macías et al., 2023) and through the ETUI Internet and Platform Work Survey (Piasna et al., 2022). A second data gap centred on the platformisation of work remains

[2] The AMPWork pilot survey is a revised third wave of the COLLEEM survey.

problematic as we discuss in the next section of this working paper. We address this problem using the available information from EU-wide statistical data and, through it, present new and original findings on how the technological transformation affects employees in terms of platformisation of work in the EU.

4 Analysing the platformisation of work

In this section, we analyse the platformisation of work as an outcome of the technological transformation. In the context of the Beyond 4.0 project, we define the technological transformation as the relationship between the inputs of the knowledge production function and its innovation outputs (Greenan and Napolitano, 2023). Building on this definition, we analyse the relationship between the technological transformation and the organisation and control of work within European companies.

The data

As noted above, the EU statistical system suffers from a data deficit that prevents it from fully capturing the socio-economic consequences of the digital transformation (Greenan and Napolitano, 2022). First, current EU surveys about the technological transformation are usually limited in scope. If they describe the adoption and use of digital technologies, they generally do not gather additional information on management and working practices and the skillsets within the organisation that underpin technological (and non-technological) innovation. The 2019 European Company Survey (ECS) is an exception. It provides a comprehensive picture of organisations' choices concerning technology adoption and use, skills management and skills utilisation, organisational practices and management tools that support individual and organisational learning as well as innovation outputs. Second, if the employer is the most appropriate informant to describe technological transformation and policy choices, the employee, worker or household are the best placed to indicate how they are affected by these company practices and developments. However, at present, the EU does not link employer-employee data at the individual level. A third limitation of existing statistical data is that they do not allow for the description of an important feature of the digital transformation – that is, the productive activities carried out via digital platforms as they impact on, even challenge, the traditional employment relationship. In particular, it is difficult to analyse how the platformisation of work affects the self-employed and employees of very small enterprises.

In an attempt to address these issues, and despite the limitations we have noted above, we built a database that combines employer and employee level surveys, the Beyond 4.0 integrated database ECS-LFS. It is an EU-wide cross-national and cross-sectoral dataset of the most recent available data, covering 2018-2019.[3]

[3] We provide more detail of this dataset in Greenan et al. (2023).

Table 1 below presents the key measures of this analysis and relates them to the survey from which it originates. At the employer level, we use data from the ECS 2019 to construct composite indicators that measure two inputs of the technological transformation: *Digital technologies adoption and use* and the *Learning capacity of the organisation*. At the employee level, the 2019 European Labour Force Survey (LFS) ad hoc module on 'Flexibility of working time' provides variables that enables the building of a measurement framework for the platformisation of work.

We combine the data from these sources by aggregating them at a common level, which is a sector within a country, differentiated by size class. Because of the coverage of the ECS, the analysis focuses on a population of enterprises with more than 10 employees in a subset of sectors.

Table 1: Key measures and related sources of data

Measures	Data source	Level of information
Technology adoption and use	European Company Survey (ECS, Eurofound), 2019	Employer
Learning capacity of the organisation		
Platformisation of work	Labor Force Survey (LFS, Eurostat), 2019 + ad-hoc module on flexibility of working time	Employee

The final dataset covers:

- 28 countries i.e., the 27 EU Member States plus the UK;
- 15 sectors (NACE Rev. 2 at 1-digit level, sectors B to N, plus R and S);
- 2 size classes: 10-50 employees and more than 50 employees.

Because some sectors are not covered in all countries or do not have both size classes, the dataset has 664 cells in total.

A measure of the platformisation of work

In section 3, we defined the 'platformisation of work' as the use of the digital technology and algorithmic management practices initially implemented by platform companies but now extending to the more standard work settings in non-platform companies. We thus want to capture work settings with a lack of control and under digital surveillance in these other companies.

Three variables from the LFS ad-hoc module on flexibility of working time structure our measurement framework for *Platformisation of work* (see Table 2 below). Two of these variables relate to the lack of control of employees over their work and tasks. A first one concerns the lack of control over time as it indicates whether the employer or organisation mainly decides on the start and end of the working time. Control of time is particularly important in algorithmic management as digital technologies direct the allocation of tasks between employees and thus their time schedule. A second variable relates to the lack of procedural autonomy as indicated by the response to a question in which employees state their level of influence on the order and content of tasks. We suggest that employees lack procedural autonomy when they indicate little or no influence. Finally, to acknowledge the presence of digital surveillance over the labour process, a third variable is integrated that accounts for the fact that hours worked are recorded automatically in a clocking system or at computer log-in, thus serving as an indicator of digitally enabled worker surveillance.

We measure *Platformisation of work* as those forms of work organisation characterised by employees' lack of time and procedural autonomy, reinforced by surveillance through digitalised systems. The indicator is 1 if the employee lacks time control, autonomy and is digitally supervised, 0 otherwise. This measure has some limitations. For instance, in the manufacturing sector, it could measure algorithmic management as well as more traditional Tayloristic work organisation.

As data are aggregated at the country-sector-size level, the final indicator refers to the percentage of employees in a specific country-sector-size level that are subject to a platformised form of work. Tables A1 and A2 in appendix report the summary statistics and correlation matrix of the overall indicator and its components.

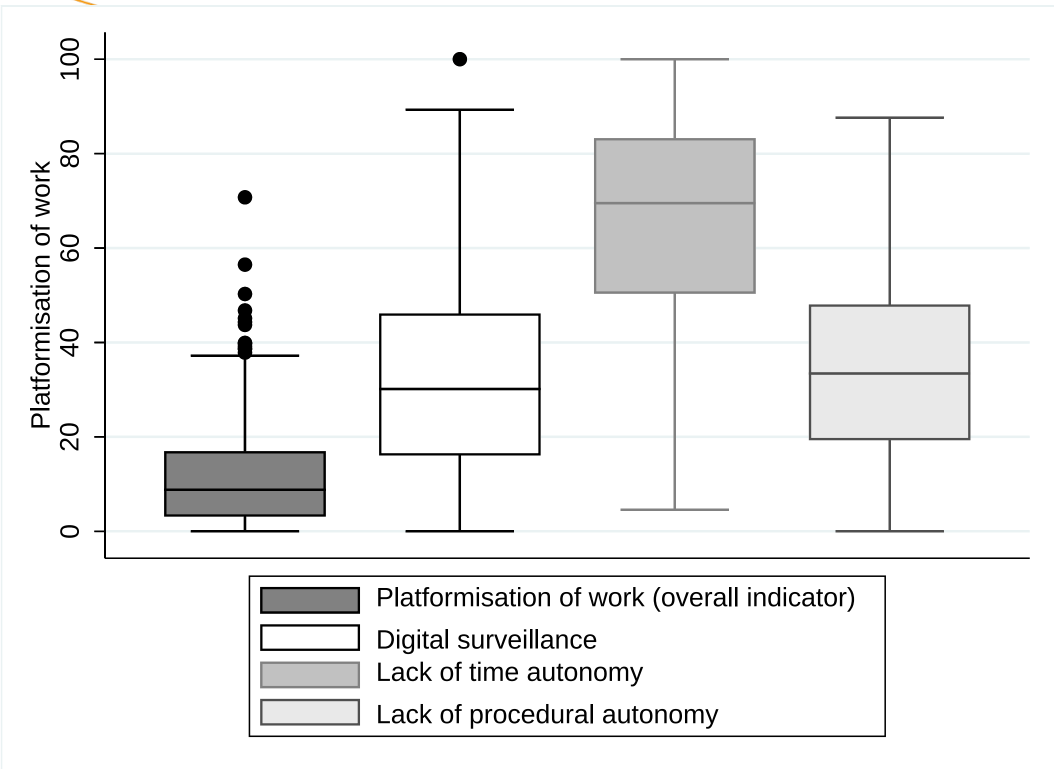
Table 2: Variables in the measurement of the platformisation of work

LACK OF TIME CONTROL	Employer or organisation mainly decides the start and end of the working time	variwt
LACK OF PROCEDURAL AUTONOMY	Employee has little or no influence on order and content of tasks	jobauton
DIGITAL SURVEILLANCE	Hours are recorded automatically (clocking system, at log-in)	rechours

Source: LFS ad hoc module 2019 on 'Flexibility of working time'

We find an average of 11 per cent of employees affected by platformised work in our dataset and some heterogeneity between country-sector-size cells (see Figure 1 below). The most widespread sub-dimension is the lack of time autonomy, which affects an average of 64 per cent of employees, while the lack of procedural autonomy and digital surveillance on average affect about one third of the workforce covered.

Figure 1: Distribution of the Platformisation of work and sub-component

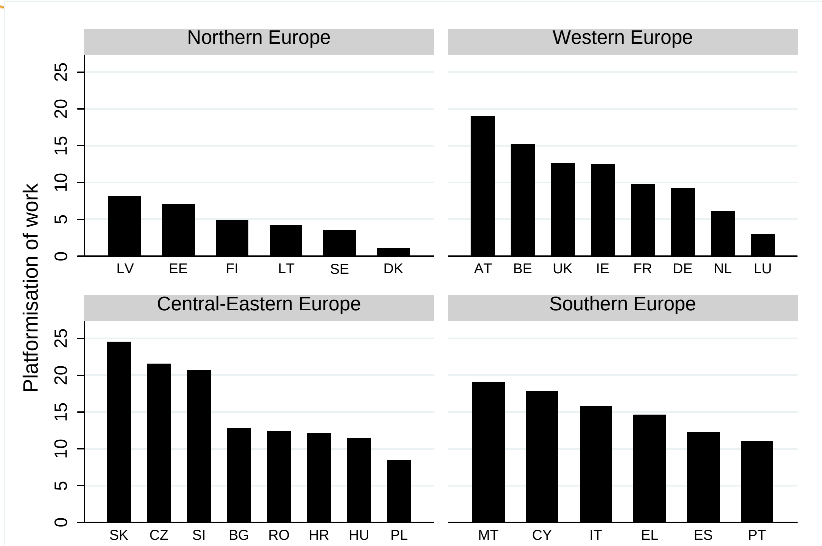


Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S.

Differences between countries and sectors are large. Northern EU countries have the lowest shares of employees subject to the platformisation of their work. Platformisation is a more prevalent form of work in Central, Eastern and Southern European countries but it is also above average in Austria, Belgium, the UK and Ireland (see Figure 2 below).

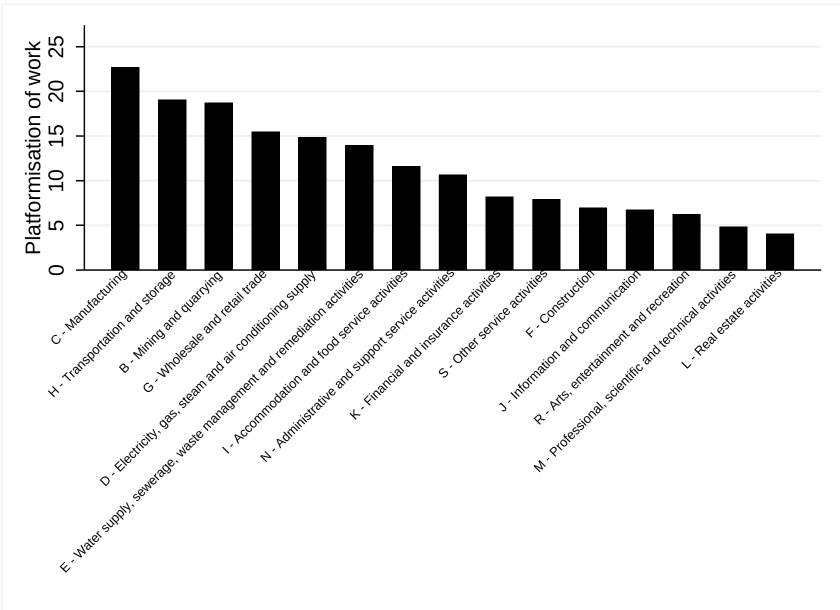
Focusing on sectors, we find the highest share of platformised work in the manufacturing sector (Figure 3). Such differences might relate to the fact that we cannot distinguish between Tayloristic and platformised forms of work. It could also reflect the fact that platformised forms of work are more likely to spread in sectors where the labour process is already highly standardised. Platformised work is also quite prevalent in transportation and storage, mining and quarrying, wholesale and retail (see Figure 3 below).

Figure 2: Platformisation of work by countries



Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S.
Note: Northern Europe LV: Latvia, EE: Estonia, FI: Finland, LT: Lithuania, SE: Sweden, DK: Denmark; Western Europe: AT: Austria, BE: Belgium, UK: United Kingdom, IE: Ireland, FR: France, DE: Germany, NL: The Netherlands, LU: Luxembourg, Central-Eastern Europe: SK: Slovakia, CZ: Czech Republic, SI: Slovenia, BG: Bulgaria, RO: Romania, HR: Hungary, PL: Poland, Southern Europe: MT: Malta, CY: Cyprus, IT: Italy, EL: Greece, PT: Portugal.

Figure 3: Platformisation of work by sectors



Source: Beyond 4.0 integrated database ECS-LFS 2019
Coverage: EU27 plus UK, enterprises with more than 10 employees in NACE Rev. 2 1-digit sectors B to N plus R and S.

Methods and results

We analyse how the *Platformisation of work* relates to organisations' strategies in terms of the adoption and the use of digital technologies, the organisation of work and the management of skills. A central question is whether the new possibilities for the automation of work processes and management functions that digital technologies offer are used by organisations to extend Taylorism to new segments of economic activity beyond manufacturing and the call centre sector and if so, whether this is connected to specific forms of innovation.

The information we use from the ECS is specific to the 2019 edition. This dataset imposes limitations on the measurement of the knowledge production function as used so far in the deliverable to describe the technological transformation. Indeed, if we are able to measure innovation inputs and outputs from this survey, information about them are collected together. Questions about inputs are related to year 2018 and questions about innovation relate to a change that occurred between 2016 and the date of the survey, which weakens the temporal ordering in causal chain. However, the *Platformisation of work* is measured in 2019 from the LFS, which ensures the exogeneity of the information provided by the ECS. We thus tested whether innovation outputs played a role together with the inputs in influencing platformised forms of work (see Table A3 in the appendix). Unlike for *Quality of working time* and *Work life balance indicators* analysed in part D, we did not find any significant effect. The Innovation output thus does not mediate the relationship between the inputs of the knowledge production function and platformised forms of work.

Therefore, in the following, we consider only the direct relationship between the inputs of interest of the knowledge production function, – *Digital technology adoption and use* and *Learning capacity of the organisation* – and the *Platformisation of work*. Empirically, we implement weighted least squares regressions, which allow us to account for the differing sizes of industries within countries (Wooldridge, 2010) by weighting each observation by the number of employees in the sector-size-country cell, estimated with data from the LFS 2019.

The model is specified as follows:

$$\text{I. } Platformisation_{isj} = \beta_0 + \beta_2 Tech_{isj} + \beta_3 Learn_{isj} + \varepsilon_{isj}$$

where i are sectors according to the NACE Rev. 2 classification at 1-digit level, s are the size-classes (10-50 employees vs 50+ employees) and j are countries.

$Platformisation_{isj}$ equals the percentage of employees in a specific sector-size-country cell that are subject to platformised work. We model the influences on platformisation of two inputs of the knowledge production function measured from the ECS, $Tech_{isj}$ and $Learn_{isj}$.[4]

$Tech_{isj}$ is the *Digital technology adoption and use* indicator: it equals the sum of the rates of diffusion in each sector-size-country cell of four technologies (e-commerce, e-business, data

[4] The measurement of these two indicators is presented in more detail in part D.

analytics and robots). Rates are weighted for the inverse of the European diffusion rate of each technology, so that technologies that are more widespread have lower weights, while emerging ones have higher ones. Table A3 in the appendix reports the variables from the ECS 2019 used to construct the composite indicator and European diffusion rates. The final indicator is normalised to vary from 0 (basic technologies adoption and use) to 100 (advanced technologies adoption and use).

$Learn_{isj}$ is the indicator for the *Learning capacity of the organisation*. It equals the average, in a specific sector-size-country cell, of seven dimensions: the preservation of the cognitive dimension of work, training opportunities, worker autonomy in cognitive tasks, stimulation of intrinsic motivation, autonomous teamwork practices, social support, supportive supervisory style and direct worker participation. These seven dimensions are weighted to provide a final indicator with weights. Values vary from 0 (no Learning capacity) to 100 (maximum Learning capacity).

To further explore the relationship, we test different models:

II. $$Platformisation_{isj} = \beta_0 + \beta_2 Tech_{isj} + \beta_3 Learn_{isj} + \beta_5 Tech{:}Learn + \varepsilon_{isj}$$

III. $$Platformisation_{isj} = \beta_0 + \beta_2 Tech_{isj} + \beta_3 Learn_{isj} + \beta_5 Tech{:}Learn + \beta_6 Y_{isj} + \varepsilon_{isj}$$

IV. $$\begin{aligned} Platformisation_{isj} = \beta_0 + \beta_3 Learn_{isj} + \beta_{11} Ecommerce_{isj} + + \beta_{11} Ebusiness_{isj} + \\ + \beta_{11} Dataanalytics_{isj} + \beta_{11} Robots_{isj} + \varepsilon_{isj} \end{aligned}$$

V. $$\begin{aligned} Platformisation_{isj} = \beta_0 + \beta_3 Learn_{isj} + \beta_{11} Ecommerce_{isj} + + \beta_{11} Ebusiness_{isj} + \\ + \beta_{11} Dataanalytics_{isj} + \beta_{11} Robots_{isj} + \beta_{12} Learn{:}Ecommerce_{isj} + \\ + \beta_{13} Learn{:}Ebusiness_{isj} + \beta_{14} Learn{:}Dataanalytics_{isj} + \beta_{15} Learn{:}Robots_{isj} + \varepsilon_{isj} \end{aligned}$$

In the second specification, we include an interaction term[5] between *Technology adoption and use* and *Learning capacity of the organisation* (Model II in Table 3 below).

In the third specification, we add the following controls (the matrix Y): the share of employees in the enterprise that have an open-ended contract and the share that have a part-time contract, the percentage of women, the percentage of employees with upper secondary and third level education and the percentage of employees by age classes. These controls are computed on LFS data from 2018 to limit the endogeneity problems by adding a one-year lag between the computation of controls and of the outcome variables. We also add as control the share of enterprises with formal employees' representation (trade unions or other employee representatives), information which is available from the ECS 2019 (model III in Table 3).

In the fourth specification, we decompose the *Technology adoption and use indicator* in its four sub-dimensions (e-business, e-commerce, data analytics and robots) in order to explore

[5] The variables $Tech_{is}$ and $Learn_{isj}$ have been centred in the interaction term so that the coefficient associated with each input corresponds to an effect at sample means when the interaction term is nil.

which technologies are most correlated with platformised forms of work and test the interaction of each of these components with the *Learning capacity* indicator (model IV and V in Table 3).

Table A4 in the appendix reports summary statistics of all variables included in the models and gives their source. In all specifications, country dummies, a dummy distinguishing between tertiary (sectors G to N plus R and S) and secondary sectors (sectors B to F) and a dummy distinguishing between small enterprises (10-50 employees) and larger enterprises (50+ employees) are also added as controls.

Our results, reported in Table 3 below, show that investments in digital technologies are associated with an increase in the percentage of employees exposed to the *Platformisation of work*: a 1-point rise in *Digital technology adoption and use* has an increasing effect on the Platformisation of work of 0.12 ppt (model II). Technologies more strongly related to the *Platformisation of work* are data analytics (0.062) and robots (0.064) (models IV).

By contrast, in sectors with higher *Learning capacity of the organisation*, a lower percentage of employees is exposed to *Platformisation of work*. In terms of magnitude, a 1-point rise in *Learning capacity* has a reducing effect on *Platformisation of work* of -0.37 percentage points (ppt) (model II).

When investments in digital technology adoption and use and learning capacity of the organisation are combined, the protective role of organisational learning capacity for employees prevails, with the results showing a significant and decreasing effect of -0.006% (model II and III). Looking at the interaction between the learning capacity of the organization and the different technologies more specifically (model V and VI), we can see that the protective role of learning capacity is maintained when combined with the use of data analytics (-0.006) and robots (-0.004) but not when combined with e-commerce technologies (0.003).

Among the additional controls (model III), we consider the share of workers with temporary contracts as well as the share of part-time workers. The purpose is to check whether the *Platformisation of work* is more frequent in sectors in which non-standard forms of employment are more widespread. Contrary to our expectation, the answer is no. We find no significant relationship with part-time work and a negative one with employment precariousness. Hence, *Platformisation of work* is associated with permanent rather than temporary jobs. Consistent with this result, we find a positive relationship between trade union presence and the *Platformisation of work*, while the presence of other employee representation is not significant. Again, this finding could reflect the importance of platformised work in manufacturing sectors where trade unions are better established. When looking at the characteristics of the workforce, we find that the percentage of women is not significantly related to the *Platformisation of work*, while a higher percentage of employees with third level education and aged between 30-44 or 60+ years is associated with lower shares of platformised forms of work. Finally, we observe a higher platformisation of work incidence in the secondary than in the tertiary sectors and in larger sized companies (50+ versus 10-50 employees).

Overall, the incidence of the platformisation of work for companies that invest in digital technologies and in particular data analytics and robotics appears to be higher. The option of leveraging this new generation of technologies to implement digitally assisted Taylorism seems attractive, especially in larger unionised manufacturing companies. However, joint investment in the learning capacity of the organisation counteracts this effect. An obvious issue is whether this effect is homogeneous across sectors and European regions. We thus test heterogeneous effects between the secondary and tertiary sector and between the North-West and the South-East of Europe.

Heterogeneous effects

The results surrounding sectoral heterogeneous effects, as reported in Table 2 below, show that the protective role of the *Learning capacity of the organisation* has similar strength in both sub-samples of tertiary and secondary sectors. By contrast, the negative effect of *Technology adoption and use* is especially evident in secondary sectors. Indeed, the estimated coefficient associated with this indicator is larger and more significant (0.161 versus 0.046 in model III). Further, we find a negative effect of the adoption and the use of data analytics and robots in the secondary sectors only. Nonetheless, the protective role of learning capacity is maintained in these sectors when combined with robots. If we find in the tertiary sector a positive effect of the *Digital technology adoption and use* indicator, it does not break down with the sub-component of the technology indicator. Furthermore, the interaction effect is not significant.

When considering the controls, the negative effect of the age group 60+ years remains across the two groups of sectors. The other effects found in the overall regression prove to be sector specific. In the secondary sector the effects of trade union presence, temporary contracts and education are no longer significant. This finding might reflect the lower number of observations, in particular for trade union presence which keeps the same positive sign while being close to significance. However, a new effect becomes significant: a higher share of women in the workforce favours the platformisation of work. Interestingly, in the tertiary sector, this effect is reversed. Otherwise, the protective effect of temporary contracts, higher education and small sized companies on the platformisation of work is confined to the tertiary sector.

When looking at the subsample of Northern and Western countries and of Southern and Central-Eastern countries shown in Table 3 below, we see that technology adoption and use has similar effects on the two sub-samples. By contrast, the protective role of learning capacity against platformised forms of work is especially relevant in terms of magnitude in Northern and Western countries while the interaction term between learning capacity and digital technology is only significant in the Southern and Central-Eastern regions.

Table 1. WLS with robust standard errors and number of employees as weights

	Percentage of employees with platformised work					
	I	II	III	IV	V	VI
Technology adoption and use	0.111***	0.116***	0.128***			
	(3.75)	(3.87)	(4.45)			
Learning capacity of organisations	-0.385***	-0.372***	-0.260***	-0.377***	-0.362***	-0.241***
	(-6.97)	(-6.69)	(-4.20)	(-6.72)	(-6.33)	(-3.79)
Learning:Technology		-0.006***	-0.006**			
		(-2.72)	(-2.69)			
E-commerce				0.012	0.010	-0.004
				(0.61)	(0.53)	(-0.18)
E-business				-0.029	-0.036	-0.026
				(-1.38)	(-1.63)	(-1.23)
Data analytics use				0.062***	0.061***	0.071***
				(3.07)	(2.94)	(3.63)
Robots				0.064***	0.079***	0.089***
				(2.59)	(2.92)	(3.42)
Learning:E-commerce					0.003*	0.003*
					(1.96)	(1.96)
Learning:E-business					-0.001	-0.001
					(-0.70)	(-0.63)
Learning:Data analytics use					-0.004**	-0.004**
					(-2.38)	(-2.38)
Learning:Robots					-0.006**	-0.006***
					(-2.57)	(-2.82)
Trade union present			0.057*			0.058*
			(1.81)			(1.82)
Other ER present			0.027			0.025
			(1.18)			(1.05)
% employees with temporary contracts			-0.135**			-0.134**
			(-2.38)			(-2.38)
% employees with part-time contracts			0.025			0.030
			(0.59)			(0.68)
% Female			-0.015			-0.020
			(-0.57)			(-0.75)
Edu: ref. Lower secondary edu						
Upper secondary edu			-0.023			-0.008
			(-0.56)			(-0.19)
Third level edu			-0.114***			-0.114***
			(-3.39)			(-3.36)
Age (ref. 15-29)						
30-44 years			-0.083*			-0.082*
			(-1.88)			(-1.82)
45-59 years			-0.032			-0.045
			(-0.82)			(-1.10)
60 or more years			-0.362***			-0.354***
			(-4.84)			(-4.54)
Tertiary sectors	-3.231***	-3.312***	-1.707	-2.631***	-2.146**	-0.347
(Ref: secondary sectors)	(-3.69)	(-3.80)	(-1.55)	(-2.80)	(-2.19)	(-0.29)
Size: 10 to 50 employees	-2.974***	-2.946***	-2.794***	-3.387***	-3.536***	-3.442***
(Ref: more than 50)	(-4.24)	(-4.21)	(-3.05)	(-4.62)	(-4.81)	(-3.73)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	35.93***	34.70***	36.03***	37.45***	35.73***	35.97***
	(11.22)	(10.42)	(6.27)	(11.59)	(10.55)	(5.96)
Observations	664	664	664	664	664	664
Adjusted R^2	0.429	0.436	0.483	0.432	0.444	0.495

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Source: Beyond 4.0 integrated database ECS – LFS 2019

Table 2. WLS with robust standard errors and number of employees as weights – by sector

	Percentage of employees with platformised work							
	Tertiary sectors				Secondary sectors			
	II	III	V	VI	II	III	V	VI
Technology adoption and use	0.055**	0.046*			0.246***	0.161**		
	(2.06)	(1.79)			(4.09)	(2.44)		
Learning capacity of organisations	-0.369***	-0.154**	-0.343***	-0.144**	-0.278*	-0.340**	0.053	0.070
	(-6.86)	(-2.53)	(-6.03)	(-2.29)	(-1.72)	(-2.08)	(0.24)	(0.34)
Learning:Technology	-0.003	-0.002			-0.009*	-0.010**		
	(-1.21)	(-1.31)			(-1.84)	(-2.03)		
E-commerce			0.003	-0.017			0.046	0.023
			(0.12)	(-0.86)			(0.79)	(0.37)
E-business			-0.004	0.012			-0.107*	-0.080
			(-0.16)	(0.60)			(-1.80)	(-1.38)
Data analytics use			0.026	0.022			0.185***	0.133***
			(1.15)	(1.19)			(4.46)	(2.88)
Robots			-0.044	-0.013			0.078**	0.058
			(-1.25)	(-0.41)			(2.08)	(1.27)
Learning:E-commerce			0.004**	0.003			0.004	0.009
			(2.12)	(1.63)			(0.94)	(1.64)
Learning:E-business			-0.004	-0.003*			-0.002	-0.002
			(-1.57)	(-1.70)			(-0.54)	(-0.57)
Learning:Data analytics use			-0.002	-0.002			-0.000	0.000
			(-1.15)	(-1.28)			(-0.02)	(0.10)
Learning:Robots			0.003	0.002			-0.018***	-0.019***
			(1.17)	(1.08)			(-3.31)	(-3.35)
Trade union present		-0.000		-0.008		0.094		0.108
		(-0.01)		(-0.28)		(1.27)		(1.55)
Other ER present		-0.026		-0.023		0.094		0.074
		(-1.20)		(-1.08)		(1.64)		(1.27)
% employees with temporary contracts		-0.104**		-0.095*		-0.187		-0.228
		(-1.99)		(-1.82)		(-0.84)		(-1.17)
% employees with part-time contracts		0.016		0.016		-0.253		-0.354
		(0.36)		(0.36)		(-1.18)		(-1.54)
% Female		-0.077***		-0.073***		0.241***		0.191**
		(-3.30)		(-3.05)		(2.87)		(2.23)
Edu: ref. Lower secondary ed								
Upper secondary edu		-0.073*		-0.060		-0.005		0.012
		(-1.86)		(-1.51)		(-0.04)		(0.10)
Third level edu		-0.175***		-0.167***		0.003		-0.013
		(-5.52)		(-5.15)		(0.03)		(-0.13)
Age (ref. 15-29)								
30-44 years		-0.037		-0.048		-0.170		-0.165
		(-0.86)		(-1.06)		(-1.17)		(-1.14)
45-59 years		-0.041		-0.057		-0.086		-0.048
		(-1.07)		(-1.39)		(-0.67)		(-0.38)
60 or more		-0.300***		-0.308***		-0.385**		-0.316*
		(-3.63)		(-3.78)		(-2.00)		(-1.91)
Size: 10 to 50 employees (Ref: more than 50)	-3.120***	-4.612***	-3.732***	-4.968***	-1.646	0.576	-2.186	0.569
	(-4.30)	(-5.17)	(-4.90)	(-5.53)	(-0.96)	(0.22)	(-1.12)	(0.20)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	34.23***	40.29***	33.80***	40.36***	22.11**	35.53**	8.449	15.14
	(9.23)	(7.71)	(8.77)	(7.31)	(2.39)	(2.13)	(0.71)	(0.92)
Observations	477	477	477	477	187	187	187	187
Adjusted R^2	0.424	0.519	0.428	0.519	0.439	0.502	0.494	0.531

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Source: Beyond 4.0 integrated database ECS – LFS 2019

Table 3. WLS with robust standard errors and number of employees as weights – by country groups

	Percentage of employees with platformised work							
	Northern and Western countries				Southern and Central-Eastern countries			
	II	III	V	VI	II	III	V	VI
Technology adoption	0.125***	0.124***			0.113**	0.135***		
and use	(3.81)	(3.66)			(2.11)	(2.79)		
Learning capacity	-0.475***	-0.312***	-0.489***	-0.319***	-0.264**	-0.194*	-0.255**	-0.166
of organisations	(-8.67)	(-4.54)	(-8.71)	(-4.38)	(-2.44)	(-1.71)	(-2.26)	(-1.44)
Learning:Technology	-0.003	-0.002			-0.012**	-0.011**		
	(-1.32)	(-1.08)			(-2.41)	(-2.17)		
E-commerce			0.025	0.010			-0.001	-0.014
			(1.00)	(0.41)			(-0.02)	(-0.48)
E-business			-0.047*	-0.025			0.001	-0.019
			(-1.76)	(-0.93)			(0.03)	(-0.51)
Data analytics use			0.090***	0.083***			0.034	0.066**
			(3.27)	(3.13)			(1.00)	(2.18)
Robots			0.039	0.054*			0.097**	0.105***
			(1.37)	(1.82)			(2.31)	(2.63)
Learning:E-commerce			0.003	0.002			0.003	0.002
			(1.20)	(1.11)			(0.84)	(0.48)
Learning:E-business			0.001	-0.000			-0.001	-0.000
			(0.74)	(-0.07)			(-0.29)	(-0.11)
Learning:Data analytics use			-0.005***	-0.004*			-0.005	-0.005
			(-2.79)	(-1.95)			(-1.33)	(-1.41)
Learning:Robots			0.000	-0.000			-0.014***	-0.013***
			(0.04)	(-0.00)			(-2.89)	(-3.24)
Trade union present		-0.021		-0.018		0.066		0.076*
		(-0.60)		(-0.50)		(1.56)		(1.76)
Other ER present		-0.001		-0.005		0.067		0.055
		(-0.05)		(-0.22)		(1.49)		(1.13)
% employees with temporary contracts		-0.126		-0.112		-0.090		-0.103
		(-1.64)		(-1.50)		(-1.19)		(-1.34)
% employees with part-time contracts		-0.028		-0.023		0.045		0.091
		(-0.65)		(-0.52)		(0.53)		(1.01)
% Female		-0.022		-0.020		0.012		-0.015
		(-0.80)		(-0.66)		(0.28)		(-0.35)
Edu: ref. Lower secondary edu								
Upper secondary edu		0.021		0.032		-0.025		-0.016
		(0.45)		(0.62)		(-0.38)		(-0.25)
Third level edu		-0.111***		-0.105**		-0.090*		-0.096*
		(-2.81)		(-2.40)		(-1.67)		(-1.82)
Age (ref. 15-29)								
30-44 years		-0.068		-0.063		-0.042		-0.063
		(-1.29)		(-1.18)		(-0.50)		(-0.72)
45-59 years		-0.087*		-0.093*		0.095		0.074
		(-1.87)		(-1.94)		(1.28)		(0.94)
60 or more		-0.119		-0.086		-0.565***		-0.590***
		(-1.38)		(-0.94)		(-5.43)		(-5.31)
Tertiary sectors	-0.680	0.677	-0.570	0.969	-6.549***	-4.767***	-4.259**	-1.870
(Ref: secondary sectors)	(-0.80)	(0.58)	(-0.56)	(0.75)	(-4.40)	(-2.77)	(-2.56)	(-1.03)
Size: 10 to 50 employees	-1.327*	-2.257**	-2.044**	-2.942**	-4.555***	-3.144**	-4.889***	-3.545**
(Ref: more than 50)	(-1.69)	(-1.97)	(-2.58)	(-2.57)	(-3.98)	(-2.21)	(-3.99)	(-2.42)
Country dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	38.19***	38.49***	41.20***	39.49***	35.80***	18.65	32.98***	22.37**
	(10.73)	(6.57)	(10.90)	(6.50)	(7.02)	(1.62)	(5.86)	(2.01)
Observations	353	353	353	353	311	311	311	311
Adjusted R^2	0.488	0.531	0.501	0.541	0.350	0.413	0.356	0.425

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Source: Beyond 4.0 integrated database ECS – LFS 2019

Nonetheless, when breaking down the indicator of *Technology adoption and use*, we find that data analytics comes out strongly in the Northern and Western regions, both in terms of a direct effect favouring the platformisation of work and of a protective effect when interacted with learning capacity, while robots drive similar effects in the South and Central-East regions. The added controls are less significant than in the sectoral analysis, with the exception of higher education and small company size, which protect against the platformisation of work in the two groups of regions while the share of employees aged 60+ years and the tertiary sector have a protective effect in Southern and Central-Eastern countries only.

5 Conclusion and discussion

What Beyond 4.0 refers to as the 'digitalisation of work', manifest in 'platform work', has rightly become a concern for policymakers and researchers. However, it could well be that very few workers in the EU are involved in platform work either as a sole or a supplementary source of income. Nonetheless, the same application of algorithmic management that is applied to organise and control the tasks of platform workers can be extended to employees in non-platform companies. This 'platformisation of work' is likely to affect a much larger number of EU workers.

Although there is a data deficit in the EU that hinders the analysis of this potential extension, in this working paper, we develop a novel composite indicator using the best possible available data from two sources – the LFS and the ECS. Our analysis reveals that 11 per cent of employees within the EU are subject to the platformisation of work, though there are differences within the EU based on the geographical clustering of countries. In sectors where the platformisation of work is more stringent, employees experience a loss of task and time autonomy. We find that the technologies that are the more strongly related to the platformisation of work are data analytics and robots. Nevertheless, where there is greater organisational learning capacity, employees are less likely to experience the platformisation of their work. This algorithmic management is a hybrid of technical and bureaucratic control, mixing new digital technology with new rules, or at least procedures, that determine the organisation of work. Just as with platform work (Pesole et al., 2018; Kellogg et al., 2020), the use of algorithms by managers is opaque and strips employees of the control of their work.

Our estimate of 11 per cent of employees within the EU being subject to platformisation of work generally aligns with results from the JRC AMPWork pilot survey, in which the working populations in Spain and Germany were classified into four different categories based on use (no use) of digital tools and the presence (absence) of algorithmic management, digital monitoring or both (Fernandez-Macias et al., 2023:36).[6] Sectoral differences in the degree of platformisation of work were also found in AMPWork pilot.[7]

Our findings need to be qualified by recognition of the data deficit. As Greenan and Napolitano (2022) note, this deficit can be addressed, firstly, through the collection of data that includes the management and working practices and skill sets within organisations that underpin technological and non-technological innovation, and, secondly, through the linking of employer and employee level data on the drivers and outcomes of such innovations. As they also note though, this data deficit exists not just for the platformisation of work but also for platform work, though the latter is now being addressed. It would be very useful if further, substantive methodological and conceptual attention was focused on the platformisation of work. Doing so would also lead to collecting more information on how the technological transformation is challenging the traditional employment relationship and how productive activities in digitally operated networks shape it.

Notwithstanding the data deficit, our findings show that there is likely to be five times as many more employees in non-platform companies subject to algorithmic management than there are workers who might to some extent engage in platform work (11% vs around 2% respectively). This greater coverage deserves serious policy consideration. It is right that the European Commission has responded to concerns about the use of algorithmic management with platform workers. However, our findings suggest that the European Commission should also consider the use of algorithmic management amongst employees in the traditional economy. Policy intervention here might both be more needed and have a greater impact for more workers.

The use of algorithmic management seems detrimental to job quality at a time when the European Commission is encouraging more better jobs as well as seeking an upward convergence of job quality across EU countries (Warhurst et al., 2020). Such policy would also align with and further the European Pillar of Social Rights, particularly the part of Chapter II that promotes fair working conditions.[8] In light of our findings, it seems that broader regulation is required to regulate all work, not just platform work. As Murray and Stewart (2015: 41) explain, employment law is needed because if working conditions are left to the 'higgling of the market', then 'socially undesirable and unjust outcomes' will result. It is the role of the state to set minimum standards, Murray and Stewart continue. Regulation of the employment relationship represents 'the principal vehicle for the allocation of labour rights' (Countouris, 2019: 10) and 'a gateway to social protection' (Forde et al., 2017: 67); it falls to the European Commission to set these standards to protect workers. It is noteworthy that,

[6] Using their categorisation, the JRC pilot estimated that ten per cent of German and 18 per cent of Spanish workers were under mild forms of digital monitoring and algorithmic management ('soft platformisation') and one per cent of German workers and six per cent of Spanish workers were under strong forms of both digital monitoring and algorithmic management ('strong platformisation').
[7] High technology industries (HTI) having the highest levels of both strong and soft forms of platformisation, followed by Knowledge Intensive Services (KIS).
[8] https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/economy-works-people/jobs-growth-and-investment/european-pillar-social-rights/european-pillar-social-rights-20-principles_en

through the new Digital Services Act[9], the European Commission is keen to protect consumers from inappropriate capture by algorithms but does not yet recognise the need to prevent the inappropriate control of employees as workers by those algorithms. Given the opacity when it comes to the use of algorithms by companies (Pesole et al., 2018), strong consumer protection needs to be matched by good worker protection underpinned by the same type of transparency and accountability framework as that set out in the Digital Services Act.

Such protections may also be helpful for companies as algorithmic management may be dysfunctional for employers. There can be unforeseen and unanticipated problematic consequences within companies that apply algorithmic management, just as there was when scientific management was first introduced. Dissatisfaction arose out of scientific management from both workers and managers. For workers, as scientific management defined their tasks and duties, it stripped them of their task discretion and control over their work. It also cheapened their labour and, through deskilling, made workers substitutable. In turn, this development homogenised these workers and collectivised their interests, leading to the formation of large-membership industrial trade unions (Edwards, 1979). For managers, scientific management provided a legitimacy of purpose and legitimised their authority. It also expanded their numbers. What is less well appreciated is that scientific management also partially challenged their supervisory discretion because it also defined managers' work. Being stripped of this discretion could be important as workers became dissatisfied with the organisation and the control over their work and the task rules were used by unions and workers to restrict what other work these workers were willing to do. When they were not willing, they 'worked to rule' which, ironically often reduced labour efficiency rather than improving it as scientific management set out to do. Moreover, as worker dissatisfaction and turnover ran high with the marriage in his factories of Taylorism and the moving assembly line in the 1920s, Ford had to significantly increase wages – his famous $5 day – in order to attract and retain employees (Beynon, 1973). In a potted history of work organisation, Thompson and McHugh (2009) observe that despite the continuing prevalence of aspects of Taylorism/scientific management, a strong narrative exists in the literature that it should be replaced because it can be dysfunctional. There may be short-term gains but, ultimately, it is less efficient for employers and undermines the wellbeing of employees. Alternatives are repeatedly offered as being more efficient, they point out. In this respect, while companies can achieve short-term gains in efficiency by using algorithmic management, these strategies favour exploitation rather than exploration and can hamper the potential for innovation. Furthermore, they risk eroding important line management relationships and dehumanising workers (Briône, 2020). As our analysis shows, promoting investments in the learning capacity of the organisation could be a way to fight against negative consequences associated with the platformisation of work.

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[9] https://ec.europa.eu/commission/presscorner/detail/en/IP_22_6906

In this respect, if policy interventions aimed to restore, even enhance, employee task and time autonomy, it would also help the EU's productivity agenda. Algorithmic management, as scientific management before it, conceptualises employees as an extension of machines and ignores the human dimension to work. Reflecting critically on the potential human costs of digitalisation and the current failure of Industrie 4.0 to deliver the anticipated productivity gains, there is already some desire within the European Commission to see a future of work that places humans at its centre. This human-centric approach is evident in the European Commission's call for a new Industry 5.0. in which 'technology serves people … placing the well-being of the industry worker at the centre of the production process' (Cotta and Breque, 2021: 15 & 3). This Industry 5.0 is premised on improving efficiency so that both companies and workers benefit from the digital transformation. It is based on technology not determining its application. It recognises that how technology is used and what effects it has on the organisation of work and the control of workers is shaped by the decisions of employers and the balance of power between employers and employees. Contrary to the belief of Taylor (1947), there is no one best way to organise work through scientific management or, we would add now, algorithmic management. During the putative '3rd Industrial Revolution', for example, when micro-chip technology was introduced to companies, how it was used to organise work varied as did workers' control of it, even amongst companies in the same industry. As Child outlines in his concept of 'strategic choice', organisational practices are the outcome of 'an essentially political process in which constraints and opportunities are functions of the power exercised by decisions makers in the light of ideological values' (1972: 22). Child focused mainly on the intra-organisational political process, most obviously between employers and employees. Clark et al. (1988) would later argue that the scope should be extended to include governments, social partners, users and providers of technology as well as the public. The European Commission thus also has a role in shaping the future of work in the presumed Digital Revolution. Addressing the platformisation work, not just platform work, has to become a policy priority with the aim of freeing Europe from the perceived constraints that technology imposes on work organisation and instead choosing which constraints to impose upon the use of technology in work.

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7 Appendix

Table A1: Platformisation of work: summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Platformisation of work	664	11,36	10,54	0,00	70,75
Digital surveillance	664	33,05	20,91	0,00	100,00
Lack of procedural autonomy	664	64,60	23,18	4,59	100,00
Lack of time autonomy	664	34,55	18,63	0,00	87,63

Table A2: Platformisation of work: correlation matrix

	Platformisation of work	Digital surveillance	Lack of procedural autonomy	Lack of time autonomy
Platformisation of work	1,00			
Digital surveillance	0,71	1,00		
Lack of procedural autonomy	0,58	0,13	1,00	
Lack of time autonomy	0,43	0,09	0,66	1,00

Table A3. WLS with robust standard errors and number of employees as weights

	Percentage of employees with platformised work			
Technology adoption and use	0.113***	0.108***	0.113***	0.119***
	(3.52)	(3.27)	(3.76)	(3.71)
Learning Capacity	-0.382***	-0.388***	-0.375***	-0.378***
	(-6.61)	(-6.71)	(-6.74)	(-6.91)
Tertiary sectors	-3.240***	-3.217***	-3.184***	-3.098***
	(-3.66)	(-3.61)	(-3.57)	(-3.56)
Size: 10 to 50 employees (ref: more than 50)	-2.966***	-2.974***	-2.890***	-2.982***
	(-4.22)	(-4.23)	(-4.07)	(-4.24)
Product innovative enterprises	-0.004			
	(-0.20)			
Process innovative enterprises		0.005		
		(0.24)		
Organisation innovative enterprises			-0.020	
			(-0.72)	
Marketing innovative enterprises				-0.018
				(-0.87)
Country dummies	yes	yes	yes	yes
Constant	35.77***	36.10***	35.60***	35.65***
	(10.80)	(10.85)	(11.06)	(11.24)
Observations	664	664	664	664
Adjusted R^2	0.429	0.429	0.429	0.429

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$;

Source: Beyond 4.0 integrated database ECS-FS 2019

Table A4: Summary statistics of the variables

Variable	Source	Obs	Mean	Std. Dev.	Min	Max
Learning Capacity	ECS 2019	664	53,57	8,58	26,29	78,10
Technology adoption and use	ECS 2019	664	45,89	16,71	0,00	100,00
E-commerce	ECS 2019	664	27,27	19,46	0,00	100,00
E-business	ECS 2019	664	52,17	19,41	0,00	100,00
Data analytics use	ECS 2019	664	56,05	22,91	0,00	100,00
Robots	ECS 2019	664	10,57	17,02	0,00	100,00
Trade union present	ECS 2019	664	9,64	16,92	0,00	93,83
Other ER present	ECS 2019	664	27,87	27,95	0,00	100,00
% employees with temporary contracts	LFS 2018	664	10,23	9,61	0,00	58,59
% employees with part-time contracts	LFS 2018	664	12,20	12,89	0,00	74,49
% female	LFS 2018	664	40,43	18,20	0,00	93,68
% employees with upper secondary edu	LFS 2018	664	49,14	18,87	0,00	88,33
% employees with third level edu	LFS 2018	664	36,90	21,25	0,00	96,17
% employees 30-44 years old	LFS 2018	664	38,98	10,87	0,00	84,78
% employees 45-59 years old	LFS 2018	664	34,58	11,73	0,00	100,00
% employees 60 or more years old	LFS 2018	664	6,48	5,65	0,00	44,97