

Skill Resilience 4EU

SkillResilience4EU

Resilience through re-skilling and upskilling for European labour markets in transition

D1.1 – Knowledge base on the impact of the twin transition on the European labour market

**DISCLAIMER:
THIS DELIVERABLE IS
PENDING EU APPROVAL.**



**Funded by
the European Union**

Project information

Project acronym:	SkillResilience4EU
Full title:	Resilience through re-skilling and upskilling for European labour markets in transition
Grant agreement:	101177821
Programme and call:	HORIZON-CL2-2024-TRANSFORMATIONS-01-03 - Minimise costs and maximise benefits of job creation and job destruction
Project coordinator:	HVL
Contact:	SkillResilience4EU@hvl.no
Project duration:	36 months
Project website:	

Deliverable information

Deliverable number	D1.1
Deliverable title:	Knowledge base on the impact of the twin transition on the European labour market
Dissemination level:	PU - Public
Deliverable type:	R — Document, report
License:	CC BY-NC-ND 4.0
Status:	Submitted
Due date:	31/03/2025
Submission date:	31/03/2025
Work Package:	1
Lead Beneficiary:	Universiteit Utrecht

Disclaimer

Funded by the European Union. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union. Neither the European Union nor the European Research Executive Agency can be held responsible for them.

All SkillResilience4EU consortium members are also committed to publish accurate and up to date information and take the greatest care to do so. However, the SkillResilience4EU consortium members cannot accept liability for any inaccuracies or omissions, nor do they accept liability for any direct, indirect, special, consequential or other losses or damages of any kind arising out of the use of this information.

Revision History

Date	Version	Author	Comment
20/02/2025	V0.01	Deyu Li, UU	Creation of document outline
17/03/2025	V0.02	Deyu Li, UU	First draft
24/03/2025	V0.03	Deyu Li, UU Ron Boschma, UU Maria Tsouri, HVL	Edit and revise of the first draft
31/03/2025	V0.03	Lars Coenen, HVL	Review of the final draft
31/03/2025	V0.04	Risk and Quality Manager, HVL	Final check and approval for submission
31/03/2025	V1.0	Coordinator, HVL	Final check and submission to the granting authority

Author List

Institution	First name and Name	Contact information
UU	Deyu Li	d.li1@uu.nl
UU	Ron Boschma	r.a.boschma@uu.nl
HVL	Maria Tsouri	maria.tsouri@hvl.no

Abbreviations and acronyms

Abbreviation or acronym used in this document	Explanation
EU	European Union
OECD	Organisation for Economic Cooperation and Development
Cedefop	European Centre for the Development of Professional Training
SBTC	Skill biased-technical change
RBTC	Routine biased-technical change
IoT	Internet of things
AI	Artificial Intelligence
ICT	Information and Communication Technologies
US	United States

LLM	Large Language Model
ESCO	European Skills, Competences, Qualifications and Occupations
J2JOD	Job-to-Job flow origin-destination

Glossary

Term	Definition used or meaning in the Acronym project	Reference or source for the definition if applicable
Climate action	It refers to efforts taken by individuals, organizations, and governments to mitigate climate change by reducing greenhouse gas emissions and adapting to its impacts to ensure environmental sustainability and resilience.	United Nations Framework Convention on Climate Change (UNFCCC) (2015). Paris Agreement.
Directed technical change model	It explains how the direction of technological progress is influenced by economic incentives, market structures, and policy interventions.	Acemoglu, D. (2002)
Job polarization	It refers to the phenomenon where employment opportunities increase at both the high-skill, high-wage and low-skill, low-wage ends of the labour market, while middle-skill, middle-wage jobs decline.	Autor, Levy, & Murnane (2003)
Lock-in	It refers to a situation where a particular technology, economic system, or institutional framework becomes entrenched, making it difficult to transition to alternative options, even when superior alternatives exist.	Arthur, W. B. (1989)
Eco-innovation	It is the development of products, processes, services, or business models that reduce environmental impacts while promoting sustainable economic growth.	Kemp, R., & Pearson, P. (2007)

Executive Summary

The transition towards a green and digital economy has been on top of the policy agenda of the European Commission in its new growth model for sustainable prosperity, fairness and competitiveness. The green transition is an opportunity for Europe to achieve sustainable and inclusive growth, as well as energy and resource security because it has the potential to in reducing energy prices and dependence on fossil fuel imports. The digital transition has the potential to offer new opportunities for people and businesses and increase the innovation and productivity of the European Union (EU) economy.

This report provides a comprehensive knowledge base on the labour market implications of digital transition and green transition based on a thorough literature review of key scientific literature, institutional reports and policy briefs, as well as deliverables from other relevant EU projects, etc. that study the labour market implications of the green and digital transitions. We focus on the empirical studies and review the theoretical foundations and main findings of these empirical studies.

Existing studies of digital and green transitions suggest heterogeneous impacts of digital and green technologies on employment across regions and sectors, and on job transitions of workers (especially displaced workers) across different social-demographic groups and skill profiles. Many mix results between different studies also raise concerns for the policy makers. More importantly, the existing literature mostly focuses on the labour market implications of digital transition and green transition separately. There is limited understanding of how digital transition and green transitions could jointly shape the future of work and influence the labour market resilience in Europe.

The gaps identified in this report help outline a comprehensive conceptual framework in guiding the upskilling and reskilling practices that should further include: 1) macro-economic conditions that will shape the type and direction of the interconnections between digital transition and green transition; 2) skill mismatches of workers (especially displaced workers) and their needs of upskilling and reskilling in a green and digital economy; 3) place-based capabilities and institutions that could facilitate or delay the twin transition and labour market resilience.

Table of Contents

1	Introduction	7
2	Theoretical models on the labour market impact of green and digital transitions	8
2.1.1	Directed technical change and the digital transition.....	8
2.1.2	Directed technical change and the green transition	9
3	Empirical evidence on the labour market impacts of digital and transitions	9
3.1	Digital transition and labour market	10
3.1.1	Measuring the adoption of digital technologies and occupation exposure.....	10
3.1.2	Labour market impact.....	10
3.1.2.1	Job creation and destruction	10
3.1.2.2	Job transitions at individual level	12
3.2	Green transition and labour market.....	12
3.2.1	From green jobs to jobs in the green economy	12
3.2.2	Labour market impact.....	13
3.2.2.1	Job creation and destruction	13
3.2.2.2	Job transitions at individual level	14
4	Areas of future work	15
4.1	Macro-economic conditions and the interconnections between digital and green transitions	15
4.2	Skill mismatches, left behind and upskilling and reskilling	16
4.3	Place-based capabilities and institutions for labour market resilience.....	16
4.3.1	Location as job transition enablers or barriers in digital and green transitions	16
4.3.2	Policy and institution for upskilling, reskilling and labour market resilience	17
5	Conclusion	18
5.1.1	Plan for Open-Access Database	18
6	References	18
7	Annex 1: The Consortium	29
	Annex 2: Project Summary	30

1 Introduction

The transition towards a green and digital economy has been on top of the policy agenda of European Commission for its new growth model¹. The green transition, driven by climate action, is an opportunity for Europe to achieve sustainable and inclusive growth, as well as energy and resource security because it could help reduce energy bills and dependence on fossil fuel imports. Simultaneously, the digital transition has the potential to create new opportunities for people and businesses, enhance climate resilience through smart technologies, and increase the innovation and productivity of the EU economy while supporting sustainable development goals.

Although the digital and green technologies have the potential in promoting economic and employment growth (OECD, 2023b, 2024b), the labour market implications and the welfare effects of the green and digital transitions are likely to be unequally disturbed across sector, region and social-demographic groups (OECD, 2023a, 2024a). The transformation of the European economy will only succeed if it is fair, inclusive and beneficial for every citizen (Dixson-Declève et al., 2023). Thus, large scale investment in reskilling and upskilling are needed to facilitate labour reallocation within and between sectors and territories in Europe to seize the opportunities and mitigate the job displacement effect of the digital and green transition (Cedefop, 2023).

Over the years, several European initiatives, such as the European Commission's 2020 skill agenda² and the European Year of skills in 2023³, were set up to support the skills and quality jobs to close the skill shortage in the EU for the digital and green transition. The importance of upskilling and reskilling have been further highlighted in the Draghi report⁴ for reinstating Europe's competitiveness, and later in the new European Commission's priority on competitiveness⁵ and its new initiative Union of Skills⁶.

However, despite the increasing policy and academic interests in 'twinning' the digital transition and the green transition for sustainable prosperity, fairness and competitiveness, their interconnections remain less explored, especially on whether and how they could jointly influence the future of work and the labour market resilience in Europe (Aloisi, 2025). In order to guide the development of a conceptual framework for labour market resilience to the digital, green and twin transitions, this report aims to build a comprehensive knowledge base on how digital transition and green transition affect the (European) labour markets, regarding the job creation and destruction, and job transitions of individual workers. Methodologically, the initial step involved a thorough search for key scientific literature, institutional reports and policy briefs, as well as deliverables from other relevant EU projects, etc. that study the labour market implications of the green and digital transitions. We mainly focus on the empirical papers that are published after 2020 and review the theoretical foundations and main findings of these empirical studies.

The remaining of this document is structured as follows. Section 2 discusses the theoretical foundations that are mostly used in analysing the labour market impacts of digital and green transitions. Section 3 turns the empirical literature. This literature traces the development and diffusion of digital and green technologies and explores their impacts on job creation and destruction, and job transitions of individual workers. Section 4 discusses the limitations of existing literature and outlines important areas of future work that could form the building blocks for a comprehensive conceptual framework of labour market resilience to green, digital and twin transitions to guide the upskilling and reskilling. Section 5 concludes.

¹ European Growth Model, https://ec.europa.eu/commission/presscorner/detail/en/ip_22_1467

² European Skill Agenda, https://employment-social-affairs.ec.europa.eu/policies-and-activities/skills-and-qualifications/european-skills-agenda_en

³ European Year of Skills, https://year-of-skills.europa.eu/index_en

⁴ Draghi Report, https://commission.europa.eu/topics/eu-competitiveness/draghi-report_en

⁵ A new plan for Europe's sustainable prosperity and competitiveness, https://commission.europa.eu/priorities-2024-2029/competitiveness_en

⁶ Unions of Skills, https://commission.europa.eu/topics/eu-competitiveness/union-skills_en

2 Theoretical models on the labour market impact of green and digital transitions

The directed technical change model has been applied the most to understand the labour market implications of digital and green transitions (Hémous & Olsen, 2021). Building on the induced innovation theory and the endogenous growth theory, Acemoglu (1998, 2002) formalized the initial ideas that changes in relative factor supply could induce bias in innovation direction. Importantly, if substitution is sufficiently easy, we get an increase in the relative supply of a factor can raise that factor's relative reward in the long run. In other words, technology becomes so biased toward the now-abundant input that its productivity (and thus wage or price) jumps, possibly reversing any initial drop in its reward. Whether technical change ends up biased toward the abundant factor or the scarce factor depends on the elasticity of substitution between factors. When inputs can easily substitute for each other (high elasticity), the market-size effect dominates: a larger supply of some input leads to more innovation that augments that input. In contrast, with low substitutability, innovation is directed more toward saving the scarce input.

Overall, the directed technical change framework provides a unifying theory to understand how economic and environment incentives shape technology, in other words, how inventors choose to direct their R&D toward augmenting specific factors or sectors by using particular inputs (like skilled labour, machine or clean energy) more intensely (Hémous & Olsen, 2021). In turn, the directed and biased technological progress will shape the future of work under both digital and green transitions.

2.1.1 Directed technical change and the digital transition

Digital transition, associated with the rise of computers, internet of things (IoT), robotics, and artificial intelligence (AI), has massively changed the demand for skills and the nature of work (Brynjolfsson & McAfee, 2014). The directed technical change model and the views of skill-biased technical change (SBTC) and routine-biased technical change (RBTC) are helpful for understanding the underlying mechanisms of how digital transition could affect the labour market (Acemoglu & Autor, 2011).

On the one hand, the digital transition is skill-biased because digital technologies such as computer, IoT, platforms and AI are mostly used by educated workforces on the job, and preferentially increase the productivity of these skilled workers relative to unskilled workers (Frey & Osborne, 2017). The skill-biased technical change (SBTC) view argues that technology enters as a factor-augmenting improvement that complements workers with higher skill or education, effectively raising their marginal productivity. The results are a rightward shift in demand for skilled workers, leading to higher relative wages for skilled workers (Acemoglu & Autor, 2011; Goldin & Katz, 1998). In essence, the SBTC proposes a race between education and technology that will favour skilled workers if technology advances faster than the workforce's skill level (Acemoglu & Autor, 2011). As shown in Acemoglu (2002), if the elasticity of substitution between skilled and unskilled labour is high, the influx of skilled workers is likely to induce more innovations that complement skilled labour. As a result, technology can become more skill-biased over time, leading to the skill premium despite an expanding skilled workforce.

On the other hand, many digital technologies, such as robotics and AI, automate tasks previously done by humans. Thus, it is important to focus on tasks performed in jobs, rather than workers' skill level per se. Over the recent years, the RBTC has been more dominant in explaining the job polarization in the era of digitalization and automation (Acemoglu & Autor, 2011; Aghion et al., 2022; Restrepo, 2024). Autor et al. (2003) provided an empirical task-based RBTC. In their framework, jobs consist of bundles of tasks (routine or non-routine, cognitive or manual), and technology may substitute for labour in some tasks while complementing labour in others. They empirically showed that computerization substitutes for routine (repetitive) cognitive and manual tasks but complements workers in non-routine problem-solving and interactive tasks.

Acemoglu and Restrepo (2018, 2019) further formalized how automation vs. new task creation could affect labour demand. According to them, the technological progress can be directed in two broad ways: (1) labour-replacing innovations (automation) that allow capital (machine or software) to perform tasks formerly performed by workers, and (2) labour-augmenting innovations that increases the productivity of

workers performing non-routine tasks, or create new tasks in which labour has a comparative advantage (often higher-skill tasks) or can complement automation technologies. The theoretical prediction is that labour-replacing innovations, such as assembly line robots and AI chatbots, will reduce the share of labour in the value added, leading to job destruction or displacement. At the same time, the digital transition also gave rise to entirely new job categories and industries, such as software development, data science, IT support, digital marketing, etc., leading to the job creation or reinstatement.

More importantly, many middle skilled jobs with high intensity of routine tasks could also be replaced by automation technologies, such as office, administrative, and production jobs, whereas some lower-education jobs (like caring or cleaning) may be relatively insulated if they require non-routine human interaction. Thus, if the directed innovation is skewed too much toward automation, we are likely to observe job polarization where these middle-skill routine jobs decline and high-skill (and some low-skill service) jobs expand (Autor & Dorn, 2013; Buyst et al., 2018).

2.1.2 Directed technical change and the green transition

Directed technical change theory has also become an important theoretical foundation for analysing how the green transition unfolds and its labour market implications (Acemoglu et al., 2012; Hémous & Olsen, 2021). The central idea is that innovation can be steered away from polluting technologies toward green technologies, and this direction will determine which sectors grow or decline, thus affecting jobs, skills, and the distribution of work across the economy.

Acemoglu et al. (2012) integrates environmental constraints into a directed technical change model. In this model, the economy produces output using a dirty input (fossil-fuel based technology) and a clean input (green technology). In the laissez-faire market, firms will direct innovation to whatever is more profitable. However, the incumbent dirty sector has had a large market and well-developed technology compared to the emerging green technology which tends to be more expensive. Without intervention, technical change towards green transition will not take place. Thus, in order to make clean technology sufficiently substitutable to fossil-fuel based technology, timely and right combination of policy incentives (like a carbon tax and clean R&D subsidy) are important to mobilize innovators to develop cleaner technologies and sustain economic growth in the long-term (Acemoglu et al., 2016).

This shift in innovation direction also indicates a sectoral transformation: the clean tech sector expands (solar, wind, energy-efficient products, electric vehicles, etc.), while the fossil-fuel sector contracts. However, the net employment effect could be ambiguous. It could be positive (if new green industries are more labour-intensive or grow faster) or negative (if automation in new green industries is high or old jobs are lost faster than new ones grow). But as long as dirty technologies dominate, there will be lock-in and path-dependence preventing the growth of green industries. Thus, it is important to break the lock-in by making clean technologies competitive (Acemoglu et al., 2012, 2016). Once that happens, technology advancement in green industries will in turn creates demand for labour in those sectors. Simultaneously, jobs in the fossil fuel sectors are likely to decline.

Furthermore, the green transition not only requires the transition from the fossil fuel-based energy sources to clean energy sources, but also requires the pollution control and restoration, improvement of energy and resource efficiency, and new solutions for negative carbon emissions. Hémous and Olsen (2021) argue that there is also the complementarity case that energy or resource saving technologies are used as an input factor. However, the labour market implications of such input-saving technical change are less clear.

3 Empirical evidence on the labour market impacts of digital and transitions

This section reviews the empirical literature exploring the implications of green and digital transition on labour market. More specifically, this section will review the implication of green transition and digital transition separately by discussing the creation and diffusion of new technologies and their impacts on the task and skill content of different occupations, job creation and destruction, and job transitions at the individual level.

3.1 Digital transition and labour market

3.1.1 Measuring the adoption of digital technologies and occupation exposure

The challenge in unfolding the labour market implications of digital transition is two folds: 1) measuring the adoption of digital technologies; 2) identifying the tasks and skills of different occupations and industries that are likely to be automated or augmented by digital technologies. Over the recent years, a large volume of empirical studies made significant contributions in these two areas (Corrocher et al., 2024; Hötte et al., 2023; Restrepo, 2024).

On the adoption of digital technologies, many studies leveraged secondary data on the adoption of computers, information and communication technologies (ICTs), robots, and AI at the industry level (Acemoglu & Restrepo, 2020; Autor & Dorn, 2013). Several studies conducted surveys to get the first-hand data on the adoption of different digital technologies at the firm level (Arntz et al., 2024). When the actual adoption data is difficult to obtain, many studies leveraged patent data to proxy the technological advancement in different digital technologies (Hémous et al., 2025; Montobbio et al., 2024a). Recent studies also proxy the adoption of digital technologies with hiring practices using online job vacancies (Acemoglu et al., 2022; Pouliakas, 2021) or the web text of companies (Dahlke et al., 2024; Kalyani et al., 2025).

On the exposure to digital technologies, Frey & Osborne (2017) was the first to construct occupational level exposure to computerization. Many recent studies leveraged patent data to construct the task-level exposure to different digital and automation technologies (Autor et al., 2024; Hémous et al., 2025; Kogan et al., 2023; Meindl et al., 2021; Montobbio et al., 2024a; Prytkova et al., 2024; Webb, 2020). Since the emergence of Generative AI such as ChatGPT, several studies constructed the occupation exposure to generative AI by investigating the tasks that can be performed by AI or large language models (LLMs) such as ChatGPT (Eloundou et al., 2023; Felten et al., 2021; Gmyrek et al., 2023; Hampole et al., 2025).

3.1.2 Labour market impact

3.1.2.1 Job creation and destruction

Autor and Dorn (2013) provided early insights into how local labour markets, particularly those specializing in routine tasks, adapted to the rise of ICTs. Their study revealed employment polarization in these local labour markets, as low-skill workers were reallocated to service occupations, while wage polarization emerged with growth concentrated at both ends of the wage distribution. Additionally, these regions attracted inflows of skilled labour, further reshaping the workforce composition. Several systematic review of the labour market implications of computerization and the rise of ICTs (Corrocher et al., 2024; Hötte et al., 2023; Montobbio et al., 2024b). They suggested that while digital technologies like computer and ICT do displace certain jobs, particularly among low-skill, production, and manufacturing workers, compensatory mechanisms often emerge to create or reinstate employment elsewhere in the economy.

Many studies focused on the job creation and destruction of robots using industry-level robots installation data from International Federation of Robotics or firm-level data on the import of robots (Guarascio et al., 2024). For example, at the industry level, Acemoglu & Restrepo (2020) studied the introduction of industrial robots across United States (US) industries in the 1990s and 2000s. They showed that US industries benefiting from advances in industrial robotics increased value added and reduced employment. Graetz & Michaels (2018) focused on a broader set of European countries with higher levels of robot adoption than the US. They showed that industries with intensive tasks that can be automated via industrial robots adopted more robots and experienced decrease in employment from 1993 to 2007.

At the regional level, Acemoglu & Restrepo (2020) showed that US commuting zones that specialized in industries experiencing significant advances in industrial robots saw a relative decline in employment and wages. Dauth et al. (2021) found comparable results in their study of German regions to Acemoglu & Restrepo (2020). However, they find no adverse effects on total regional employment, as young workers entering the labour market find jobs in the expanding business services sector. They argued that the

displacement effects from robot adoption in Germany and the US are of a similar magnitude, but in Germany, the productivity gains from automation are higher and benefit exposed labour markets the most because of the expansion of integrators and robot producers.

At the firm level, many studies documented increasing employment in firms adopting robots as well as a shift in the composition of employment away from production and routine-manual jobs and an increase in the demand for skilled labour (Restrepo, 2024). However, in a recent meta-analysis of the impact of robots on employment and wages conducted by Guarascio et al. (2024), they revealed that although on average the adoption of robots has negative and statistically significant effects on both employment and wages, these effects remain marginal and close to zero.

Turning to the more recent digital technology, AI, Webb (2020) constructed the occupational AI exposure based on the co-occurrence of verb-noun pairs in AI patents and tasks of occupations in the O*NET database from the US. He found that high-skill occupations are most exposed to AI compared to individuals with low levels of education, especially those older workers with high levels of education and accumulated experience. Felten et al. (2021) constructed their occupational exposure to AI linking human skills to most promising AI applications. They found that occupations that are most exposed to AI consist almost entirely of white-collar occupations that require advanced degrees, whereas occupations that are least exposed to AI are largely nonoffice jobs that require a high degree of physical effort and exertion.

With the emergence of LLMs, Eloundou et al. (2023) measured occupational exposure to ChatGPT based on their tasks that can be performed by ChatGPT. They revealed that around 80% of the US workforce could have at least 10% of their work tasks affected by the introduction of LLMs, while approximately 19% of workers may see at least 50% of their tasks impacted. Similar to the findings in Webb (2020), they also found that higher-income jobs potentially face greater exposure to LLM capabilities and LLM-powered software. Also focusing on the occupational exposure to Generative AI, Gmyrek et al. (2023) found higher percentage of employment that is potentially exposed to the augmentation effect of Generative AI compared to the percentage of employment that is potentially exposed to the automation effect, and the percentages are both higher in high-income countries than low-income countries.

Several studies leveraged the AI exposure scores developed by Webb (2020) and Felten et al. (2021), and studied the employment impact of AI. Both Albanesi et al. (2025) and Guarascio and Reljic (2025) found that stronger employment growth in occupations more exposed to AI in European countries. This is particularly the case for occupations with a relatively higher proportion of younger and skilled workers (Albanesi et al., 2025). Furthermore, they both found heterogeneous impacts of AI across countries. Albanesi et al. (2025) suggested that the country heterogeneity seems to be linked to the pace of technology diffusion and education, but also to the level of product market regulation (competition) and employment protection laws. They report that occupations more exposed to AI technologies display stronger employment growth compared to the rest of the workforce. Guarascio and Jelena (2025) pointed to the importance of innovative capabilities of countries in fully harnessing AI's potential for employment (and economic) growth. Guarascio et al. (2025) also found similar results focusing on the impacts of AI at the regional level in European countries.

At the firm level, due to limited information on firms' adoption of AI, many studies proxied the AI exposure with online job vacancies or patenting of firms. Aleksesva et al. (2021) documented a dramatic increase in the demand for AI skills over 2010–2019 in the US economy across most industries and occupations using detailed data on skill requirements in online vacancies. The demand is highest in IT occupations, followed by architecture and engineering, scientific, and management occupations. Acemoglu et al. (2022) further studied the impact of AI on labour markets using establishment-level data combined with the online job vacancy data in the US from 2010 onward. As firms adopt AI, they simultaneously reduce hiring in non-AI positions and change the skill requirements of remaining postings. However, they did not find significant impact of AI on employment in more exposed occupations and industries. Using a sample of 4,184 firms that patented inventions involving AI technologies, Damioli et al. (2024) found that the association between employment and AI patents is always positive and significant, despite being relatively small in terms of size.

Beyond these aforementioned studies focusing on different individual digital technologies, several studies investigated the overall employment impact of digital technologies (Meindl et al., 2021; Prytkova et al., 2024).

Prytkova et al. (2024) found a net positive impact on employment and job polarization that low- and high-skilled jobs grow at the expense of middle-skilled jobs. At the technology level, they observed significant heterogeneity which suggests the importance of complementarities among diverse digital technologies: robots and machine learning negatively impact employment (except for high-skilled workers), while workflow management and information processing systems have positive effects. However, using a similar approach, Meindl et al. (2021) suggested that fourth industrial revolution technologies may have a negative impact on job growth in the US.

Overall, the mixed results of the overall employment impacts of digital technologies such as robots and AI may arise from the different impacts on workers that are likely to be displaced in the digital transition and workers that could benefit from the digital transition (Frank et al., 2023). In this case, employment data may be uncorrelated with job losses because unemployment or job losses for an occupation can increase or decrease even as employment for that occupation increases. Given digital technologies are also changing the task and skill content of occupations, it is important to focus on the job transitions of individual workers, especially those are likely to be displaced.

3.1.2.2 Job transitions at individual level

With the availability of large-scale labour force surveys, administrative data and online worker profiles, several studies explored the impact of digital technologies on the job transitions of individual workers. Acemoglu et al. (2023) estimated the effects of robot adoption on firm-level and worker-level outcomes in the Netherlands using a linked employer-employee panel dataset spanning 2009-2020. Their worker-level results show that workers (e.g., blue-collar workers performing routine or replaceable tasks) in firms that adopted robots face lower earnings and employment rates, while other workers indirectly gain from the robot adoption. Also using the linked employer-employee data from the Netherlands, Bessen et al. (2025) found that automation increases the probability of incumbent workers separating from their employers, especially for smaller firms, and for older and middle-educated workers. By contrast, they did not find such impact of firms' investments in computers.

Cirillo et al. (2024) used an original employer-employee dataset that merges firm-level data on digital technology adoption and other characteristics of production with employee-level data on worker entry and exit rates from the administrative archive of the Italian Ministry of Labor. Their results suggested that digital technologies lead to an increase in the firm-level hiring rate, particularly for young workers, and reduce firm-level separation rate. Their results also indicated heterogeneous impacts of different digital technologies that cybersecurity, internet of things and robotics are associated with higher hiring rate for graduates, whereas no significant effects emerge for separations, except for cybersecurity which is negatively associated to firm level separation rate.

Bachmann, Gonschor, et al. (2024) studied the effects of robot exposure on worker flows in 16 European countries between 2000 and 2017. Overall, they found small negative effects on job separations and no effects on job findings. Labour cost and the intensity of routine tasks are the main drivers of differences between countries and occupations. Using the administrative data from the US, Kogan et al. (2023) showed that labour-saving technologies predict higher likelihood of job loss for all workers, labour-augmenting technologies primarily predict losses for older or highly paid workers.

3.2 Green transition and labour market

3.2.1 From green jobs to jobs in the green economy

Defining what is a green job has always been a major obstacle for empirical research on the labour market implications of green transitions (Apostel & Barslund, 2024; Vona, 2021). The most common used measure of green jobs is to focus on the jobs in the firms and sectors that (mainly) produce products or provide services that are important for the green transitions. Conversely, dirty jobs would refer to jobs in firms and sectors that (mainly) produce products or provide services that generate harmful impacts for the environment (Elliott & Lindley, 2017). This approach could capture the job creation and destruction effect of the green transition. The main limitation of this approach is that it does not allow to identify the specific

types of workers and tasks that complement green activities, limiting the possibility to analyse distributional impacts. For example, the value chain of a green product may involve different occupations (Dominish et al., 2019). Some sectors also produce both green and brown products, e.g. the automobile sector producing both internal combustion engine vehicles and electric vehicles. Furthermore, data on green production are only mostly available for the manufacturing sector, while many green jobs are created outside manufacturing in construction, waste management and power generation, etc.

Following the task-based approach proposed by Autor et al. (2003), Vona et al. (2018) defines the greenness of an occupation based on the intensity of green tasks among all tasks workers in the focal occupation performs using the US O*NET. Vona (2021) further applied the task-based approach to skills using the European Skills, Competences, Qualifications and Occupations (ESCO) database. The advantage of the task-based or skill-based approach is that it made the comparison between task or skill content between green jobs and brown jobs and tasks and skills that complement green jobs (Bowen et al., 2018; Consoli et al., 2016). It could also help provide a comprehensive evaluation of the greenness of the labour market and potential job transition pathways from brown jobs and to green jobs.

The task-based measure of green jobs is not without limitations. Most importantly, the identification of green tasks becomes crucial. Due to the limitations of available granular employment data, many green jobs identified in Vona et al. (2018) and Vona (2021) contribute to both green and brown activities, whereas many non-green occupations that could contribute to the green economy were excluded (Villani et al., 2025). Many scholars therefore propose to focus on the skills and jobs that are important for the green transition regardless the greenness of jobs (Burger et al., 2019; Buyukyazici & Quatraro, 2025). With the recent availability of large scale data such as online job posts (Sato et al., 2023; Saussay et al., 2022) and online worker resumes (Curtis et al., 2024), and linked employee-employer administrative data (Barreto et al., 2024), it would be possible to combine the two aforementioned approach in better understanding the jobs in the green economy.

3.2.2 Labour market impact

3.2.2.1 Job creation and destruction

The application of directed technical change model in green transition suggests the job growth in the green industries and decline of fossil fuel industries. Applying the task-based approach in identifying green jobs, Vona et al. (2018, 2019) found no impact of the changes in environmental regulation on overall employment. However, the changes in environment regulation stimulates the demand for some green skills, especially those related to technical and engineering work tasks. Furthermore, they found that green employment is pro-cyclical, highly skilled, commands a four percent wage premium and is geographically concentrated. Marin & Vona (2019) focused on the associations between climate policies, proxied by energy prices, and workforce skills for 14 European countries and 15 industrial sectors over the period 1995–2011. They found that climate policies have been skill biased against manual workers and have favoured technicians.

Following the similar task-based approach, Elliott et al. (2024) and Bachmann, Janser, et al. (2024) used the linked employer–employee administrative dataset from the Netherlands and Germany respectively to examine the employment impact of green transition. Elliott et al. (2024) showed that while eco-innovation does not impact overall employment, eco-product innovation does lead to a 19.72% increase in green jobs in the Netherlands. The growth in green jobs mainly comes from a compositional shift towards a small yet significant increase in green workers and reduction in non-green workers, especially in those firms that voluntarily undertake eco-innovation. Bachmann, Janser, et al. (2024) showed that both the increasing share of green tasks within occupations and the increasing share of occupations in total employment are important for the growth of the greenness of employment in Germany between 2012 and 2022. However, they didn't find the same compositional effect with respect to worker and establishment characteristics as shown in Elliott et al. (2024).

Several studies focus particularly on the green transition of the energy intensive sectors in the US and Europe combining occupation skill profiles database such as O*NET in the US and the European Skills, Competences, Qualifications and Occupations (ESCO) with employment data. Lim et al. (2023) found that

the green energy revolution may displace 1.7 million fossil fuel workers in the US. Zaussinger et al. (2025) mapped the labour market exposure to the low-carbon transition across European regions and sectors. They found that workers in high-carbon jobs lacking industry decarbonization options (at-risk jobs) have significantly fewer skills and that their skills are less transversal compared with low-carbon or neutral jobs. Their results suggested that effective deployment of industry decarbonization options helps reduce the number of at-risk workers from 6.2 million to 2.3 million. However, there are large variations between regions and sectors. For example, while at-risk jobs are most frequent in the mining sector in relative terms (11%), the manufacturing sector is most affected in absolute terms (0.9 million). Among European countries, Germany and Hungary face a particular challenge with a disproportionately high share of their workforce at risk.

As with the availability of large-scale online job vacancy data, several studies explored the job creation in key green industries. Saussay et al. (2022) provided evidence on the characteristics of low-carbon jobs in the US using comprehensive online job postings data between 2010-2019. They identified low-carbon jobs and compared them to similar jobs in the same occupational group. Their results showed that low-carbon jobs have higher skill requirements across a broad range of skills, especially technical ones. However, the wage premium for low-carbon jobs has declined over time and the geographic overlap between low- and high-carbon jobs is limited. Also using the online job posts in the US in the similar period, Curtis & Marinescu (2023) found that both solar and wind job postings have more than tripled since 2010. Solar jobs are mostly (33%) in sales occupations and in the utilities industry (16%). Wind jobs are most represented among installation and maintenance occupations (37%) and in the manufacturing industry (29%). Green jobs are created in occupations that are about 21% higher paying than average, especially for jobs with a low educational requirement. Conversely to Saussay et al. (2022), Curtis and Marinescu (2023) found green jobs tend to locate in counties with high shares of employment in fossil fuel extraction. Fackler et al. (2024) showed that from mid-2019, postings of firms that focused on the electric vehicles have consistently exceeded those firms focusing on internal combust engine vehicles, eventually being about twice as high by the end of 2023.

3.2.2.2 *Job transitions at individual level*

Over the recent years, many studies have explored the impact of green transitions on the job transitions of individuals regarding their likelihood of being unemployed and finding new jobs. Curtis et al. (2024) leveraged more than 130 million online work profiles⁷ to study the job transitions of workers employed in carbon-intensive and non-carbon-intensive jobs in the US. Their results suggest that despite the significantly increased transition rate from dirty to green jobs over the period 2005–21, less than one percent of all workers who leave a dirty job appear to make the transition to a green job. More specifically, older workers and those without a college education are less likely to switch to green jobs and more likely to other dirty jobs, other jobs, or unemployment. Bachmann, Janser, et al. (2024) found that direct job transitions to greener occupations are relatively rare in Germany. Workers in relatively brown occupations have relatively higher chances of being unemployed than workers in relatively green occupations. Furthermore, foreign workers and workers with low education are at a higher risk of being negatively affected by the green transition than other worker groups.

Barreto et al. (2024) provided a comprehensive analysis of the costs of job displacement in energy-intensive industries using harmonised linked employer-employee data from 14 OECD countries. Their findings suggest that workers displaced from energy supply and heavy manufacturing industries tend to be older and less skilled. They experience larger earnings losses after the displacement compared with workers in non-energy-intensive and transport sectors, mainly due to weaker re-employment outcomes in terms of wages and job instability but also challenges with finding another job. The heterogenous labour market impacts of green transitions across sectors have also been documented in Hedne (2024). Using a linked employer-employee data from Norway, Hedne (2024) showed that firms in manufacturing increased their share of high-skilled workers in response to an imported green technology shock, while firms in most other sectors (such as construction) decreased their skill ratio, implying that the labour demand and income

⁷ They used the detailed textual data on job title, firm name, occupation, and industry in the online worker profiles to define carbon-intensive jobs and non-carbon-intensive jobs.

inequality effects of green technologies vary significantly depending on the sector where the green transition occurs.

Besides the social-demographic factors such as age, education and ethnicity, the skill distance between dirty jobs and green jobs is the main barriers for successful job transitions. Lim et al. (2023) explored whether the skill similarity between fossil fuel occupations with green industry occupations and other industry occupations using the occupation skill profiles from the O*NET database and the Job-to-Job flow origin-destination (J2JOD) data by the US Census Bureau. They found that despite being relatively more similar to green industry occupations than other industry occupations, the job transition away from fossil fuel occupations is less likely unless it is to occupations with very similar skill content. Similar results are also found in Brunetti et al. (2025) which investigated the job transitions and skill alignment in Italy's green transition. They showed that skill distance negatively correlates with occupational mobility. More specifically, moving toward green occupations alleviates this negative correlation, while moving away from brown occupations does not interplay with skill distance.

Many studies also pointed out that location is a barrier for the job transition from dirty or brown jobs to green jobs. Lim et al. (2023) found that geographical distance is the main factor that prevent the occupation mobility away from the fossil fuel occupations in the US due to the spatial mismatch between job opportunities in green industries and current employment in fossil fuel industries. Curtis et al. (2024) also found the persistence of employment within dirty industries in some states in the US that more than half of all transitions out of dirty jobs are into other dirty jobs. These results suggest the importance of a place-based approach in creating job opportunities and support the upskilling and reskilling for workers that are likely to be affected by the green transition.

4 Areas of future work

The theoretical models and empirical evidence reviewed in the previous two sections provide qualitative support for the labour market implications of digital transition and green transition. However, a comprehensive conceptual framework is needed for understanding the labour market implications of digital, green and twin transitions. First, it is important to understand how macro-economic conditions will shape the direction of digital and green transitions, and particularly their interconnections. Second, it is important to further focus on the skill mismatches for identifying left-behind groups and incentives for behaviour change. Third, there is a need for the place-based approach for better identifying the capabilities, policies and institutions in creating quality job opportunities and supporting upgrading and redesigning of training and education programs for upskilling and reskilling.

4.1 Macro-economic conditions and the interconnections between digital and green transitions

The political feasibility of digital and green transitions crucially depends on whether they can facilitate the smart, sustainable and just growth (Iammarino et al., 2019; Rodríguez-Pose & Bartalucci, 2024). Thus, to fully understand the labour market resilience of European regions and sectors, it is important to understand how macro-economic conditions will affect the direction of digital and green transitions and their interconnections in influencing the labour markets.

First, existing studies suggest that the labour market implications of green transition will differ in different transition pathways (Bücker et al., 2025; Lim et al., 2023; Zaussinger et al., 2025). Furthermore, there are significant heterogeneities in the green transitions of different sectors. Hedne (2024) suggested that the green transition is not inherently skill-biased, instead, the labour demand and income inequality effects of green technologies vary significantly depending on the sector where the green transition occurs. For example, many existing studies consider the jobs in carbon-intensive sectors such as steel and cement at risk (Barreto et al., 2024). However, the adoption of green hydrogen and carbon capture and storage could facilitate the net-zero transitions of these sectors without displacing workers in these sectors (Zaussinger et al., 2025).

Second, digital technologies could also play an important role in enabling green transition, such as smart grids, digital twins, carbon management system etc. (Bachtrögler-Unger et al., 2023; Popp et al., 2024). However, existing studies mostly analyse the labour market implications of digital transition and green transition separately (Aloisi, 2025). Many studies on the twin transition do not focus on the labour market implications (Bachtrögler-Unger et al., 2023; Diodato et al., 2023; Veugelers et al., 2023). Thus, it is important to focus on the conditions that the job creation in digital transition can also mitigate the job destruction and facilitate job creation in green transitions.

4.2 Skill mismatches, left behind and upskilling and reskilling

Although existing literature suggested overall positive employment impacts of both digital and green transitions, there might be labour market frictions that displaced workers might face difficulties in transferring into new jobs created in the digital transition or green transition. Theoretically, the directed technical change model does not consider individual workers' job transition induced by the technological change in digital transition or green transition (Hémous & Olsen, 2021). Empirically, workers displaced from fossil fuel industries may not have the skills immediately required in emerging green sectors (Bücker et al., 2025; Zaussinger et al., 2025). For instance, a coal miner's skill set is not directly transferable to a wind turbine technician's job. Similarly, workers perform mainly routine tasks will also have difficulties transferring into jobs that perform a lot of non-routine cognitive tasks (del Rio-Chanona et al., 2021; Frank et al., 2019).

This is even more crucial when the skills of the displaced workers become redundant or obsolete due to technological change. The skill mismatch of these displaced workers set them on paths with job instability, permanently low earning, and left behind (Barreto et al., 2024; McGuinness et al., 2018; Neffke et al., 2024). At the regional level, if a large number of workers in a region experience similar consequences of job displacement and left-behind, it might create political instability and the rise of populism which will impede the future transitions (Rodríguez-Pose, 2018; Rodríguez-Pose et al., 2023).

Both digital transition and green transition are significantly and rapidly changing the task and skill content of jobs (Consoli et al., 2016; Restrepo, 2024). To mitigate the negative impacts of skill mismatch and left-behindness, it is important to identify the job transition pathways that could leverage the current skills of the displaced workers (Bücker et al., 2025; del Rio-Chanona et al., 2021; Zaussinger et al., 2025). If the skill gap is too large, customized training programs are needed to support the upskilling and reskilling of these displaced worker (McGuinness et al., 2018; Nedelkoska & Quintini, 2018).

4.3 Place-based capabilities and institutions for labour market resilience

4.3.1 Location as job transition enablers or barriers in digital and green transitions

Many existing studies suggest heterogeneous impacts of digital and green transitions across the local labour markets in Europe (Dauth et al., 2021; Guarascio et al., 2024, 2025; Hanna et al., 2024; Zaussinger et al., 2025). Research on the job transitions of individuals also suggest that certain groups of workers who are exposed to the job destruction of digital and green transitions are less likely to transit into new jobs, especially in their previous working locations (Barreto et al., 2024; Curtis et al., 2024; del Rio-Chanona et al., 2021; Lim et al., 2023). This is mainly because of the spatial mismatch between displaced workers and quality job opportunities. On the one hand, Bilal (2023) suggested that regions with high unemployment rate usually lack productive employers that can provide quality jobs whereas productive employers tend to concentrate. On the other hand, Atalay et al. (2024) found that jobs in larger local labour markets involve greater interpersonal interactions and have higher requirements for digital skills. These job opportunities are less exposed to the job-displacement effect of digital and green transitions.

Thus, the ability of regions to attract and create productive firms and provide quality job opportunities will become crucial for the local labour market resilience in the digital and green transitions. The evolutionary economic geography literature has highlighted the importance of local capabilities in the creation of new industries and new jobs (Boschma, 2017; Henning et al., 2025; Neffke et al., 2011). Thus, to address the challenges, it is important not only to focus on whether regions can successfully leveraging their existing

capabilities in developing new economic activities in the green and digital transitions, but more importantly to focus on whether these new economic activities can provide job opportunities for local workers who might face the job-displacement or left behind in the green and digital transitions.

Adopting such a capability approach on the geography of the Twin Transition, Bachtrögler-Unger et al. (2023) showed that European regions differ widely in their capabilities to develop new green and digital technologies. Their study found that the more developed EU regions are better equipped for developing technologies that digitize and green the economy. Developed regions also stand out in that their highest potential is concentrated in high-complex rather than low-complex green and digital technologies. This gives more developed regions a significant competitive advantage, as complex technologies are difficult to master and to imitate for other regions and therefore create higher economic returns. In contrast, transition regions and less developed regions in Europe are responsible for modest shares of twin transition patents. Their technological profiles also look different: their potential is in green rather than digital technologies, and more often in low-complex rather than high-complex technologies. Those regions find it hard to develop twin transition technologies as relevant capabilities are often missing: local firms tend to lack absorptive capacity, the regional work force tends to have inadequate skills, and/or regional institutions tend to be weak. This implies that the prospects for economic cohesion do not look that bright. With their sets of technological capabilities, more developed regions are more likely to develop further twin transition technologies, thus pulling ahead from their less developed counterparts. However, some transition, and less developed regions have some potentials to develop twin transition technologies, especially green technologies, even if these are often not the most complex ones. Overall, policymakers should refrain from supporting twin transition technologies for which their region lacks relevant capabilities.

The study of Bachtrögler-Unger et al. (2023) also investigated the role of inter-regional linkages for the Twin Transition. Instead of developing new technologies on their own, European regions could connect with other regions to access the technological capabilities they lack but are key to developing twin transition technologies. This study found that more developed regions have many more inter-regional linkages than transition and less developed regions. However, on the whole, European regions are collaborating only to a limited extent, and they do so mainly within national borders and with regions that do not have the perfect set of complementary capabilities. This may be attributed to many factors: local firms may lack information on relevant capabilities and potential cooperation partners outside their own regions, especially in other countries. Much of the research infrastructure in Europe remains organized on a national scale, while research, innovation and green policies are often uncoordinated between European member states. Cultural differences between countries in Europe (in terms of language, norms and business practices) may also play a role. The untapped potential in collaborations between European regions when it comes to developing technologies for the twin transition seems huge. Matching these complementary capabilities across regional and national borders could lead to technologies that can promote the twin transition. Bachtrögler-Unger et al. (2023) argued that policymakers should focus on unlocking the unrealized potential of stronger inter-regional collaboration and removing bottlenecks that hamper the exploitation of these opportunities.

4.3.2 Policy and institution for upskilling, reskilling and labour market resilience

As indicated in the theoretical directed technical change and empirical evidence, the labour market resilience in the digital and green transitions will critically depend on the alignment of policies from different aspects. First, innovation policies are needed to support the development and deployment of new digital and green technologies to achieve the growth potential (Dixson-Declève et al., 2023). In supporting the deployment of green technologies, climate and energy policies will also play an important role (Bücker et al., 2025; Lim et al., 2023; Marin & Vona, 2019; Zaussinger et al., 2025).

Second, labour market regulations are needed in order to protect workers' rights in the digital and green transitions, (Aloisi, 2025). More importantly, training and education policies are needed to support the upskilling and reskilling workers, especially displaced workers in order to narrow their skill mismatches with employers (Cirillo et al., 2024; Cnossen et al., 2024; Guo et al., 2022; Langer et al., 2023).

Given the complexity in the policy mixes for a resilient labour market in the digital and green transition, it is important to focus on the dynamics of institutions and actors involved, particularly at the regional level.

This is even more so because the place-based policies at the European level, the Cohesion Policies is a policy mix that covers many aforementioned aspects (European Commission: Directorate-General for Regional and Urban Policy, 2024). The successful upskilling and reskilling practices will critically depend on the coherence of policy mixes and the alignment of institutions and actors involved.

5 Conclusion

The realization of the growth potential of digital and green transitions for sustainable prosperity, fairness and competitiveness critically depends on whether the digital and green transitions can jointly facilitate the creation of quality job opportunities and smooth job transitions for workers, especially those displaced workers, from different social-demographic groups across different sectors and regions in Europe.

The mapping of existing empirical studies and their theoretical foundations suggest that existing literature mostly focuses on the labour market implications of digital transition and green transition separately. Heterogeneous impacts of digital and green technologies on employment across regions and sectors, and job transitions of workers (especially displaced workers) across different social-demographic groups and skill profiles have been documented in both digital transition and green transition. The mixed results mainly rise from 1) different measures of the exposure to new digital and green technologies, 2) different unit of analysis (i.e. industry-level, country or region-level, firm-level or individual-level).

Overall, the gap in the understanding of the interconnections between digital transition and green transition in affecting labour markets poses great challenges for the resilience of European labour markets, especially for places and groups that are more likely to be left behind. In order to guide the (re-)designing and updating education and training programs for upskilling and reskilling, a comprehensive conceptual framework is needed that further includes: 1) macro-economic conditions that will shape the type and direction of the interconnections between digital transition and green transition; 2) skill mismatches of workers (especially displaced workers) and their needs of upskilling and reskilling in a green and digital economy; 3) place-based capabilities and institutions that could facilitate or delay the twin transition and labour market resilience.

5.1.1 Plan for Open-Access Database

To further advance the understanding of the impact of the twin transition on labour markets, jobs and skills, and in line with the objectives of WP1, we will compile all reviewed academic articles into an Open Access database. We will integrate this resource at the final stage of WP1, to ensure broader accessibility and contribute to the ongoing discourse on the labour market implications of the twin transition.

6 References

- Acemoglu, D. (1998). Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality*. *The Quarterly Journal of Economics*, 113(4), 1055–1089.
<https://doi.org/10.1162/003355398555838>
- Acemoglu, D. (2002). Directed Technical Change. *The Review of Economic Studies*, 69(4), 781–809.
<https://doi.org/10.1111/1467-937X.00226>
- Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The Environment and Directed Technical Change. *American Economic Review*, 102(1), 131–166. <https://doi.org/10.1257/aer.102.1.131>
- Acemoglu, D., Akcigit, U., Hanley, D., & Kerr, W. (2016). Transition to Clean Technology. *Journal of Political Economy*, 124(1), 52–104. <https://doi.org/10.1086/684511>

- Acemoglu, D., & Autor, D. (2011). Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of Labor Economics* (Vol. 4, pp. 1043–1171). Elsevier. [https://doi.org/10.1016/S0169-7218\(11\)02410-5](https://doi.org/10.1016/S0169-7218(11)02410-5)
- Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial Intelligence and Jobs: Evidence from Online Vacancies. *Journal of Labor Economics*, 40(S1), S293–S340. <https://doi.org/10.1086/718327>
- Acemoglu, D., Koster, H. R. A., & Ozgen, C. (2023). *Robots and Workers: Evidence from the Netherlands* (Working Paper No. 31009). National Bureau of Economic Research. <https://doi.org/10.3386/w31009>
- Acemoglu, D., & Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 108(6), 1488–1542. <https://doi.org/10.1257/aer.20160696>
- Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2), 3–30. <https://doi.org/10.1257/jep.33.2.3>
- Acemoglu, D., & Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6), 2188–2244. <https://doi.org/10.1086/705716>
- Aghion, P., Antonin, C., Bunel, S., & Jaravel, X. (2022). The Effects of Automation on Labor Demand: A Survey of the Recent Literature. In *Robots and AI*. Routledge.
- Albanesi, S., Dias da Silva, A., Jimeno, J. F., Lamo, A., & Wabitsch, A. (2025). New technologies and jobs in Europe*. *Economic Policy*, 40(121), 71–139. <https://doi.org/10.1093/epolic/eiae058>
- Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, 71, 102002. <https://doi.org/10.1016/j.labeco.2021.102002>
- Aloisi, A. (2025). *Integrating the EU Twin (Green and Digital) Transition? Synergies, Tensions and Pathways for the Future of Work* (No. JRC140964). European Commission: Joint Research Centre. https://publications.jrc.ec.europa.eu/repository/bitstream/JRC140964/JRC140964_01.pdf
- Apostel, A., & Barslund, M. (2024). Measuring and characterising green jobs: A literature review. *Energy Research & Social Science*, 111, 103477. <https://doi.org/10.1016/j.erss.2024.103477>

- Arntz, M., Genz, S., Gregory, T., Lehmer, F., & Zierahn-Weilage, U. (2024). *De-Routinization in the Fourth Industrial Revolution—Firm-Level Evidence* (Working Paper No. 16740). IZA Discussion Papers. <https://www.econstor.eu/handle/10419/295763>
- Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, 159, 157–160. <https://doi.org/10.1016/j.econlet.2017.07.001>
- Atalay, E., Sotelo, S., & Tannenbaum, D. (2024). The Geography of Job Tasks. *Journal of Labor Economics*, 42(4), 979–1008. <https://doi.org/10.1086/725360>
- Autor, D., Chin, C., Salomons, A., & Seegmiller, B. (2024). New Frontiers: The Origins and Content of New Work, 1940–2018*. *The Quarterly Journal of Economics*, 139(3), 1399–1465. <https://doi.org/10.1093/qje/qjae008>
- Autor, D., & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5), 1553–1597. <https://doi.org/10.1257/aer.103.5.1553>
- Autor, D., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration*. *The Quarterly Journal of Economics*, 118(4), 1279–1333. <https://doi.org/10.1162/003355303322552801>
- Bachmann, R., Gonschor, M., Lewandowski, P., & Madoń, K. (2024). The impact of Robots on Labour market transitions in Europe. *Structural Change and Economic Dynamics*, 70, 422–441. <https://doi.org/10.1016/j.strueco.2024.05.005>
- Bachmann, R., Janser, M., Lehmer, F., & Vonnahme, C. (2024). *Disentangling the Greening of the Labour Market: The Role of Changing Occupations and Worker Flows*. <https://doi.org/10.4419/96973277>
- Bachtrögler-Unger, J., Balland, P.-A., Boschma, R., & Schwab, T. (2023). Technological Capabilities and the Twin Transition in Europe. Opportunities for Regional Collaboration and Economic Cohesion. *WIFO Studies*.
- Barreto, C., Fluchtmann, J., Hijzen, A., Lombardi, S., Bennett, P., Bertheau, A., Chan, W., Gorshkov, A., Hambur, J., Johnstone, N., Lochner, B., Meekes, J., Mehdi, T., Muraközy, B., Nolan, G., Salvanes, K., Skans, O. N., & Vejlin, R. (2024). *The “clean energy transition” and the cost of job displacement in energy-intensive industries*. OECD. <https://doi.org/10.1787/abf614d1-en>

- Bessen, J., Goos, M., Salomons, A., & van den Berge, W. (2025). What Happens to Workers at Firms that Automate? *The Review of Economics and Statistics*, 107(1), 125–141.
https://doi.org/10.1162/rest_a_01284
- Bilal, A. (2023). The Geography of Unemployment*. *The Quarterly Journal of Economics*, 138(3), 1507–1576.
<https://doi.org/10.1093/qje/qjad010>
- Bonfiglioli, A., Crinò, R., Gancia, G., & Papadakis, I. (2025). Artificial intelligence and jobs: Evidence from US commuting zones*. *Economic Policy*, 40(121), 145–194.
<https://doi.org/10.1093/epolic/eiae059>
- Boschma, R. (2017). Relatedness as driver of regional diversification: A research agenda. *Regional Studies*, 51(3), 351–364. <https://doi.org/10.1080/00343404.2016.1254767>
- Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018). Characterising green employment: The impacts of ‘greening’ on workforce composition. *Energy Economics*, 72, 263–275.
<https://doi.org/10.1016/j.eneco.2018.03.015>
- Brunetti, I., Frattini, F. F., Kuntze, M., Ricci, A., & Vona, F. (2025). *Exploring skills in the green transition: New insights from Italian data world*.
- Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company.
- Bücker, J., Rio-Chanona, R. M. del, Pichler, A., Ives, M. C., & Farmer, J. D. (2025). Employment dynamics in a rapid decarbonization of the US power sector. *Joule*, 9(2).
<https://doi.org/10.1016/j.joule.2024.12.004>
- Burger, M., Stavropoulos, S., Ramkumar, S., Dufourmont, J., & van Oort, F. (2019). The heterogeneous skill-base of circular economy employment. *Research Policy*, 48(1), 248–261.
<https://doi.org/10.1016/j.respol.2018.08.015>
- Buyst, E., Goos, M., & Salomons, A. (2018). Job polarization: An historical perspective. *Oxford Review of Economic Policy*, 34(3), 461–474. <https://doi.org/10.1093/oxrep/gry003>
- Buyukyazici, D., & Quatraro, F. (2025). The skill requirements of the circular economy. *Ecological Economics*, 232, 108559. <https://doi.org/10.1016/j.ecolecon.2025.108559>

- Cedefop. (2023). *Skills in transitions: The way to 2035*. Publications Office of the European Union.
<https://data.europa.eu/doi/10.2801/438491>
- Cirillo, V., Mina, A., & Ricci, A. (2024). Digital technologies, labor market flows and training: Evidence from Italian employer-employee data. *Technological Forecasting and Social Change*, 209, 123735.
<https://doi.org/10.1016/j.techfore.2024.123735>
- Cnossen, F., Piracha, M., & Tchente, G. (2024). Learning the Right Skill: Vocational Curricula and Returns to Skills. *Journal of Labor Economics*, 730123. <https://doi.org/10.1086/730123>
- Consoli, D., Marin, G., Marzocchi, A., & Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, 45(5), 1046–1060.
<https://doi.org/10.1016/j.respol.2016.02.007>
- Corrocher, N., Moschella, D., Staccioli, J., & Vivarelli, M. (2024). Innovation and the labor market: Theory, evidence, and challenges. *Industrial and Corporate Change*, 33(3), 519–540.
<https://doi.org/10.1093/icc/dtad066>
- Curtis, E. M., & Marinescu, I. (2023). Green Energy Jobs in the United States: What Are They, and Where Are They? *Environmental and Energy Policy and the Economy*, 4, 202–237.
<https://doi.org/10.1086/722677>
- Curtis, E. M., O’Kane, L., & Park, R. J. (2024). Workers and the Green-Energy Transition: Evidence from 300 Million Job Transitions. *Environmental and Energy Policy and the Economy*, 5, 127–161.
<https://doi.org/10.1086/727880>
- Dahlke, J., Beck, M., Kinne, J., Lenz, D., Dehghan, R., Wörter, M., & Ebersberger, B. (2024). Epidemic effects in the diffusion of emerging digital technologies: Evidence from artificial intelligence adoption. *Research Policy*, 53(2), 104917. <https://doi.org/10.1016/j.respol.2023.104917>
- Damioli, G., Van Roy, V., Vértessy, D., & Vivarelli, M. (2024). Drivers of employment dynamics of AI innovators. *Technological Forecasting and Social Change*, 201, 123249.
<https://doi.org/10.1016/j.techfore.2024.123249>
- Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 19(6), 3104–3153.
<https://doi.org/10.1093/jeea/jvab012>

- del Rio-Chanona, R. M., Mealy, P., Beguerisse-Díaz, M., Lafond, F., & Farmer, J. D. (2021). Occupational mobility and automation: A data-driven network model. *Journal of The Royal Society Interface*, 18(174), 20200898. <https://doi.org/10.1098/rsif.2020.0898>
- Diodato, D., Huergo, E., Moncada-Paternò-Castello, P., Rentocchini, F., & Timmermans, B. (2023). Introduction to the special issue on “the twin (digital and green) transition: Handling the economic and social challenges”. *Industry and Innovation*, 30(7), 755–765. <https://doi.org/10.1080/13662716.2023.2254272>
- Dixon-Declève, S., Dunlop, K., Renda, A., Charveriat, C., Christophilopoulos, E., Balland, P.-A., Isaksson, D., Martins, F., Mir Roca, M., Pedersen, G., Schwaag Serger, S., Soete, L., Stres, Š., Gołębiowska-Tataj, D., Walz, R., & Huang, A. (2023). *Industry 5.0 and the future of work: Making Europe the centre of gravity for future good quality jobs*. Publications Office of the European Union. <https://data.europa.eu/doi/10.2777/685878>
- Dominish, E., Briggs, C., Teske, S., & Mey, F. (2019). Just Transition: Employment Projections for the 2.0 °C and 1.5 °C Scenarios. In S. Teske (Ed.), *Achieving the Paris Climate Agreement Goals: Global and Regional 100% Renewable Energy Scenarios with Non-energy GHG Pathways for +1.5°C and +2°C* (pp. 413–435). Springer International Publishing. https://doi.org/10.1007/978-3-030-05843-2_10
- Elliott, R. J. R., Kuai, W., Maddison, D., & Ozgen, C. (2024). Eco-innovation and (green) employment: A task-based approach to measuring the composition of work in firms. *Journal of Environmental Economics and Management*, 127, 103015. <https://doi.org/10.1016/j.jeem.2024.103015>
- Elliott, R. J. R., & Lindley, J. K. (2017). Environmental Jobs and Growth in the United States. *Ecological Economics*, 132, 232–244. <https://doi.org/10.1016/j.ecolecon.2016.09.030>
- Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). *GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models* (No. arXiv:2303.10130). arXiv. <https://doi.org/10.48550/arXiv.2303.10130>
- European Commission: Directorate-General for Regional and Urban Policy. (2024). *Forging a sustainable future together: Cohesion for a competitive and inclusive Europe : report of the High Level Group on the Future of Cohesion Policy, February 2024*. Publications Office of the European Union. <https://data.europa.eu/doi/10.2776/974536>

- Fackler, T. A., Falck, O., Goldbeck, M., Hans, F., & Hering, A. T. (2024). The Slow End of the ICE Age in Germany: Insights from Job Postings on the Automotive Industry's Trajectory. *EconPol Forum*, 25(6), 49–56.
- Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195–2217. <https://doi.org/10.1002/smj.3286>
- Frank, M. R., Ahn, Y.-Y., & Moro, E. (2023). *AI exposure predicts unemployment risk* (No. arXiv:2308.02624). arXiv. <https://doi.org/10.48550/arXiv.2308.02624>
- Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., & Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences*, 116(14), 6531–6539. <https://doi.org/10.1073/pnas.1900949116>
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Gmyrek, P., Berg, J., & Bescond, D. (2023). *Generative AI and Jobs: A Global Analysis of Potential Effects on Job Quantity and Quality* (SSRN Scholarly Paper No. 4584219). <https://doi.org/10.2139/ssrn.4584219>
- Goldin, C., & Katz, L. F. (1998). The Origins of Technology-Skill Complementarity*. *The Quarterly Journal of Economics*, 113(3), 693–732. <https://doi.org/10.1162/003355398555720>
- Graetz, G., & Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics*, 100(5), 753–768. https://doi.org/10.1162/rest_a_00754
- Guarascio, D., Piccirillo, A., & Reljic, J. (2024). *Will robot replace workers? Assessing the impact of robots on employment and wages with meta-analysis* (Working Paper No. 1395). GLO Discussion Paper. <https://www.econstor.eu/handle/10419/282318>
- Guarascio, D., & Reljic, J. (2025). AI and employment in Europe. *Economics Letters*, 112183. <https://doi.org/10.1016/j.econlet.2025.112183>

- Guarascio, D., Reljic, J., & Stöllinger, R. (2025). Diverging paths: AI exposure and employment across European regions. *Structural Change and Economic Dynamics*, 73, 11–24. <https://doi.org/10.1016/j.strueco.2024.12.010>
- Guo, Y., Langer, C., Mercorio, F., & Trentini, F. (2022). Skills mismatch, automation, and training: Evidence from 17 European countries using survey data and online job ads. *EconPol Forum*, 23(5), 11–15.
- Hampole, M., Papanikolaou, D., Schmidt, L. D. W., & Seegmiller, B. (2025). *Artificial Intelligence and the Labor Market* (Working Paper No. 33509). National Bureau of Economic Research. <https://doi.org/10.3386/w33509>
- Hanna, R., Heptonstall, P., & Gross, R. (2024). Job creation in a low carbon transition to renewables and energy efficiency: A review of international evidence. *Sustainability Science*, 19(1), 125–150. <https://doi.org/10.1007/s11625-023-01440-y>
- Hedne, M. H. (2024). *Is green technological change skill biased?*
- Hémous, D., & Olsen, M. (2021). Directed Technical Change in Labor and Environmental Economics. *Annual Review of Economics*, 13, 571–597. <https://doi.org/10.1146/annurev-economics-092120-044327>
- Hémous, D., Olsen, M., Zanella, C., & Dechezleprêtre, A. (2025). Induced Automation Innovation: Evidence from Firm-level Patent Data. *Journal of Political Economy*, 734778. <https://doi.org/10.1086/734778>
- Henning, M., Eriksson, R., Garefelt, P., Martin, H., & Elekes, Z. (2025). Job relatedness, local skill coherence and economic performance: A job postings approach. *Regional Studies, Regional Science*, 12(1), 95–122. <https://doi.org/10.1080/21681376.2025.2459148>
- Hötte, K., Somers, M., & Theodorakopoulos, A. (2023). Technology and jobs: A systematic literature review. *Technological Forecasting and Social Change*, 194, 122750. <https://doi.org/10.1016/j.techfore.2023.122750>
- Iammarino, S., Rodriguez-Pose, A., & Storper, M. (2019). Regional inequality in Europe: Evidence, theory and policy implications. *Journal of Economic Geography*, 19(2), 273–298. <https://doi.org/10.1093/jeg/lby021>

- Kalyani, A., Bloom, N., Carvalho, M., Hassan, T., Lerner, J., & Tahoun, A. (2025). The Diffusion of New Technologies*. *The Quarterly Journal of Economics*, qjaf002. <https://doi.org/10.1093/qje/qjaf002>
- Kogan, L., Papanikolaou, D., Schmidt, L. D. W., & Seegmiller, B. (2023). *Technology and Labor Displacement: Evidence from Linking Patents with Worker-Level Data* (Working Paper No. 31846). National Bureau of Economic Research. <https://doi.org/10.3386/w31846>
- Langer, C., Peiffer, J., & Wiederhold, S. (2023). Apprenticeship skills pay off on the labor market. *EconPol Forum*, 24(6), 39–43.
- Lim, J., Aklin, M., & Frank, M. R. (2023). Location is a major barrier for transferring US fossil fuel employment to green jobs. *Nature Communications*, 14(1), Article 1. <https://doi.org/10.1038/s41467-023-41133-9>
- Marin, G., & Vona, F. (2019). Climate policies and skill-biased employment dynamics: Evidence from EU countries. *Journal of Environmental Economics and Management*, 98, 102253. <https://doi.org/10.1016/j.jeem.2019.102253>
- McGuinness, S., Pouliakas, K., & Redmond, P. (2018). Skills Mismatch: Concepts, Measurement and Policy Approaches. *Journal of Economic Surveys*, 32(4), 985–1015. <https://doi.org/10.1111/joes.12254>
- Meindl, B., Frank, M. R., & Mendonça, J. (2021). *Exposure of occupations to technologies of the fourth industrial revolution* (No. arXiv:2110.13317). arXiv. <https://doi.org/10.48550/arXiv.2110.13317>
- Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2024a). Labour-saving automation: A direct measure of occupational exposure. *The World Economy*, 47(1), 332–361. <https://doi.org/10.1111/twec.13522>
- Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2024b). The empirics of technology, employment and occupations: Lessons learned and challenges ahead. *Journal of Economic Surveys*, 38(5), 1622–1655. <https://doi.org/10.1111/joes.12601>
- Nedelkoska, L., & Quintini, G. (2018). Automation, skills use and training. *OECD Social, Employment and Migration Working Papers*, Article 202. <https://ideas.repec.org/p/oec/elsaab/202-en.html>
- Neffke, F., Henning, M., & Boschma, R. (2011). How Do Regions Diversify over Time? Industry Relatedness and the Development of New Growth Paths in Regions. *Economic Geography*, 87(3), 237–265. <https://doi.org/10.1111/j.1944-8287.2011.01121.x>

- Neffke, F., Nedelkoska, L., & Wiederhold, S. (2024). Skill mismatch and the costs of job displacement. *Research Policy*, 53(2), 104933. <https://doi.org/10.1016/j.respol.2023.104933>
- OECD. (2023a). *Job Creation and Local Economic Development 2023: Bridging the Great Green Divide*. OECD Publishing.
- OECD. (2023b). *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*. OECD Publishing. <https://doi.org/10.1787/08785bba-en>
- OECD. (2024a). *Job Creation and Local Economic Development 2024: The Geography of Generative AI*. OECD Publishing. <https://doi.org/10.1787/83325127-en>
- OECD. (2024b). *OECD Employment Outlook 2024: The Net-Zero Transition and the Labour Market*. OECD Publishing. <https://doi.org/10.1787/ac8b3538-en>.
- Popp, D., Vona, F., Grégoire-Zawilski, M., & Marin, G. (2024). The Next Wave of Energy Innovation: Which Technologies? Which Skills? *Review of Environmental Economics and Policy*, 18(1), 45–65. <https://doi.org/10.1086/728292>
- Pouliakas, K. (2021). *Artificial intelligence and job automation: An EU analysis using online job vacancy data*. (No. No.6; Cedefop Working Paper). Publications Office of the European Union. <https://data.europa.eu/doi/10.2801/305373>
- Prytkova, E., Petit, F., Li, D., Chaturvedi, S., & Ciarli, T. (2024). *The Employment Impact of Emerging Digital Technologies* (No. 10955). CESifo Working Paper. <https://doi.org/10.2139/ssrn.4739904>
- Restrepo, P. (2024). Automation: Theory, Evidence, and Outlook. *Annual Review of Economics*, 16, 1–25. <https://doi.org/10.1146/annurev-economics-090523-113355>
- Rodríguez-Pose, A. (2018). The revenge of the places that don't matter (and what to do about it). *Cambridge Journal of Regions, Economy and Society*, 11(1), 189–209. <https://doi.org/10.1093/cjres/rsx024>
- Rodríguez-Pose, A., & Bartalucci, F. (2024). The green transition and its potential territorial discontents. *Cambridge Journal of Regions, Economy and Society*, 17(2), 339–358. <https://doi.org/10.1093/cjres/rsad039>
- Rodríguez-Pose, A., Terrero-Dávila, J., & Lee, N. (2023). Left-behind versus unequal places: Interpersonal inequality, economic decline and the rise of populism in the USA and Europe. *Journal of Economic Geography*, 23(5), 951–977. <https://doi.org/10.1093/jeg/lbad005>

- Sato, M., Cass, L., Saussay, A., Vona, F., Mercer, L., & O’Kane, L. (2023). *Skills and wage gaps in the low-carbon transition: Comparing job vacancy data from the US and UK*.
- Saussay, A., Sato, M., Vona, F., & O’Kane, L. (2022). *Who’s fit for the low-carbon transition?: Emerging skills and wage gaps in job and data*. Fondazione Eni Enrico Mattei (FEEM).
<https://www.jstor.org/stable/resrep44011>
- Veugelers, R., Faivre, C., Rückert, D., & Weiss, C. (2023). The Green and Digital Twin Transition: EU vs US Firms. *Intereconomics*, 58(1), 56–62. <https://doi.org/10.2478/ie-2023-0010>
- Villani, D., Vázquez, I. G., & Fernández-Macías, E. (2025). *Green Jobs. A critique of the occupational approach to measure the employment implications of the green transition* (No. JRC140967; JRC Working Papers Series on Labour, Education and Technology). European Commission.
- Vona, F. (2021). *Labour markets and the green transition: A practitioner’s guide to the task based approach*. Publications Office of the European Union.
- Vona, F., Marin, G., & Consoli, D. (2019). Measures, drivers and effects of green employment: Evidence from US local labor markets, 2006–2014. *Journal of Economic Geography*, 19(5), 1021–1048.
<https://doi.org/10.1093/jeg/lby038>
- Vona, F., Marin, G., Consoli, D., & Popp, D. (2018). Environmental Regulation and Green Skills: An Empirical Exploration. *Journal of the Association of Environmental and Resource Economists*, 5(4), 713–753.
<https://doi.org/10.1086/698859>
- Webb, M. (2020). The impact of artificial intelligence on the labor market. *Available at SSRN 3482150*.
- Zaussinger, F., Schmidt, T. S., & Egli, F. (2025). Skills-based and regionally explicit labor market exposure to the low-carbon transition in Europe. *Joule*, 9(2). <https://doi.org/10.1016/j.joule.2024.101813>

7 Annex 1: The Consortium

Short name	Full name	Homepage	Logo
HVL	Western Norway University of Applied Sciences	https://www.hvl.no/en/	
BOKU	BOKU University	https://boku.ac.at/en/	
LSE	London School of Economics	https://www.lse.ac.uk/	
UoC	University of Crete	https://www.uoc.gr/en/	
UW	University of Warsaw	https://en.uw.edu.pl/	
UU	University of Utrecht	https://www.uu.nl/en	
FHNW	University of Applied Sciences and Arts Northwestern Switzerland	https://www.fhnw.ch/en/	
BFI	Berufsförderungsinstitut Wien	https://www.bfi.wien/	
Simplon	Simplon.co	https://www.simplon.co/	
MOP	Municipality of Platánias	https://www.platanias.gr/en/	

Annex 2: Project Summary

SkillResilience4EU - Resilience through re-skilling and upskilling for European labour markets in transition.

The twin transition (defined as the coexistence and interplay of the green and digital transitions) has enormous impacts on European labour markets. Because the green and digital transformations can feed into, facilitate, or hinder each other, it has been difficult to predict how labour markets will absorb and respond to changes and disruptions in employment conditions, skill needs and job availability and mobility. Other ongoing global challenges and macro-economic events, like the COVID-19 pandemic, also contribute to a profound reshaping of labour markets in Europe. New sectors emerge, existing sectors need to adapt and transform. New skills need to be developed or need to be transferred from other industries. Regions and sectors need to narrow labour market and skill mismatches to minimise the costs and to maximise the benefits of job destruction and job creation processes.

Different sectors and regions are affected in varying ways and intensities, either by green or digital transitions, or the combined impact of the twin transition. This unequal distribution of job creation and destruction processes may favour or leave behind places, sectors, and socio-economic groups and may threaten social cohesion and inclusion. The institutional and policy context needs to become more flexible and responsive to cope with the ongoing transformations and narrow down the labour market mismatches. Tailored and cost-effective policies and programmes for reskilling and upskilling, in particular for the most vulnerable and left-behind socio-demographic groups and places, need to be developed together with policy makers, VET providers, unions, public authorities, and other decision makers.

Funded by Horizon Europe, the European Union's Framework Programme for Research and Innovation, SkillResilience4EU will introduce a novel conceptual framework to describe and understand the impacts of the twin transition on European labour markets and will investigate the complex mechanisms, dynamics, and challenges that regions and institutions undergo by exploring selected sectors (tourism, food, transport, agriculture, and energy). The project will develop a management tool for policy makers to support them in managing labour markets in transition with recommendations for policy scenarios. SkillResilience4EU will also map and evaluate educational and training programmes for upskilling and re-skilling and will deliver recommendations and practical resources to support individuals and employers with specific focus on career guidance and development.

To achieve this ambition, the SkillResilience4EU consortium unites higher educational institutions (Western Norway University of Applied Sciences, Utrecht University, London School of Economics, University of Warsaw, University of Natural Resources and Life Sciences in Vienna, University of Crete, North-Western Switzerland University of Applied Sciences) one vocational training institute (BFI), one private training organization (Simplon.co) and a local public authority (Municipality of Plataniyas). The partners cover a whole range of expertise: economic geography, innovation studies, regional development, sustainability transitions, qualitative research, institutional research, policy research, labour and behavioural economics, education, arts and design, social inclusion, VET and lifelong learning. Coordinated by Western Norway University of Applied Sciences, the project was launched on 1st January 2025 and will run for 3 years.