

The green transition and reskilling needs

Authors: Federico Fabio Frattini, Piotr Lewandowski, Karol Madoń, Francesco Vona

Reviewer: Ronald Bachmann

Grant agreement no. 101132581

Deliverable: D4.6 Paper green transition and tasks

Due date: 30.09.2026



Funded by
the European Union

Document control sheet

Project Number:	101132581
Project Acronym:	SkiLMeeT
Work-Package:	4
Last Version:	30.09.2026
Issue Date:	30.09.2026

Classification

Draft	
Final	X
Confidential	
Restricted	
Public	X

Keywords: Green Jobs, AI Exposure, Skills Demand, PIAAC

Legal notice

This project has received funding from the European Union's Horizon 2022 Research and Innovation programme under grant agreement No. 101132581. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the granting authority can be held responsible for them. This work was produced using data from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) making use of the PIAAC Remote Code Execution Service. The views expressed are those of the author(s) and do not necessarily reflect those of the OECD or its member countries.

Table of contents

1. Introduction	5
2. Data and measurement.....	6
2.1. Greenness exposure	7
2.2. Country classification by green patent stocks	7
2.3. AI exposure	8
2.4. RTI	8
2.5. Social Skill Index	9
3. Econometric approach	9
4. Descriptive evidence.....	10
5. Econometric evidence	12
6. Conclusions	16
References	17
Appendix	19

Abstract

The green transition and the diffusion of artificial intelligence (AI) are reshaping labour markets at the same time, but it is unclear whether they affect the same workers. We study the relationship between occupational greenness and the task content of jobs using worker-level data from two cycles of PIAAC for 27 countries. We combine the task-based measure of occupational greenness of Vona et al. (2018) with worker-level measures of AI exposure, routine task intensity and social skills, and group countries by their green patent stocks per capita. Greener occupations are less exposed to AI. This association arises mostly between broad occupational groups and is driven by a few manual occupations with high greenness and low AI exposure, such as electrical trades workers, drivers and refuse workers. Within 2-digit occupational groups, greener occupations remain slightly less exposed to AI. The negative association weakened between 2011–2018 and 2022–2023, as AI exposure rose more in greener occupations. It is steeper in countries leading in green innovation, but this difference disappears within occupations. Greenness is not robustly related to routine task intensity or social skills. Overall, the green and AI transitions largely involve different parts of the workforce.

1. Introduction

The green and digital transformations are reshaping labour markets through different channels. The transition to a low-carbon economy shifts labour demand towards occupations and skills required to design, install and maintain green technologies (Vona et al., 2018; Vona et al., 2019). The digital transformation, recently accelerated by rapid advances in AI, expands the scope of automation to cognitive tasks that were less exposed to previous waves of technological change (Felten et al., 2021; Lewandowski et al., 2025). Although both transformations are high on the European policy agenda, they are typically studied separately. Yet whether green and AI exposure are concentrated among the same workers matters for policy. If green and AI-exposed jobs overlap, the same workers may face simultaneous adjustment pressures; if they do not, skills policies must reach distinct groups of workers. In either case, an effective policy response requires understanding how the two transformations intersect.

We address this gap by examining the relationship between occupational greenness and three task-based dimensions of work. We use worker-level survey data from two cycles of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), covering 2011–2018 and 2022–2023. We measure occupational greenness using the task-based index of Vona et al. (2018), defined as the share of green-specific tasks among all tasks in an occupation. We focus on three dimensions of task content: AI exposure (Lewandowski et al., 2025), routine task intensity (RTI; Lewandowski et al., 2022) and social skill use, measured by the Social Skill Index (SSI; Lewandowski & Madoń, 2026). Importantly, all three measures are derived from the tasks that workers actually perform and therefore capture differences in task content both within occupations and across countries. We also classify the 27 countries as Leaders, Adopters or Laggards according to their green patent knowledge stocks per capita and examine whether the relationships differ across these groups and between the two survey cycles.

We find that occupational greenness is negatively associated with AI exposure. Across two-digit occupations, the correlation between greenness and AI exposure is -0.33 . This relationship is largely driven by a few manual occupational groups that combine high greenness with low AI exposure: electrical and electronic trades workers, drivers and mobile plant operators, and refuse workers. Conditional on workers' human capital and country fixed effects, a one-standard-deviation increase in greenness is associated with 0.10 SD lower AI exposure. The coefficient falls by over 90% after two-digit occupation fixed effects are included but remains negative and significant, indicating that, within broad occupational groups, greener occupations are slightly less exposed to AI. The negative gradient

weakened between the two PIAAC cycles, as AI exposure increased relatively more in greener occupations. It is also about 50% steeper in Leader countries than in Laggards, although this difference disappears after accounting for broad occupational differences. By contrast, greener occupations have slightly higher routine task intensity and lower social skill use on average, but both associations disappear within two-digit occupational groups.

Our analysis contributes to two strands of literature. The first studies the skill content of green jobs, showing that green occupations require more cognitive, interpersonal and technical skills than non-green ones (Consoli et al., 2016; Vona et al., 2018). The second measures workers' exposure to AI (Felten et al., 2021) and, more recently, how it varies across countries and within occupations (Lewandowski et al., 2025). We bring the two together, using task-based measures that account for cross-country differences in the task content of jobs, and document how the green and AI transitions relate to each other in countries at different stages of green innovation.

The remainder of the deliverable is structured as follows. Section 2 describes the data and the measures of greenness, AI exposure, RTI and social skills, as well as the classification of countries. Section 3 presents the econometric approach. Section 4 reports descriptive evidence and Section 5 the econometric results. Section 6 concludes.

2. Data and measurement

We use worker-level survey data from two cycles of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), a cross-national survey that assesses adults' proficiency in basic skills, including literacy, numeracy, and problem solving. In addition to these assessments, PIAAC collects detailed information on respondents' occupations, sectors of employment, and tasks performed at work. This combination allows us to link workers' directly assessed basic skills with their occupational characteristics and work-related tasks. The latter are particularly important for our analysis, as they allow us to construct worker-level measures of AI exposure, routine task intensity, and social skills that account for differences in task content both within occupations and across countries.

Our sample covers employed individuals aged 16–65 in 27 countries participating in both PIAAC Cycle 1 (2011–2018) and Cycle 2 (2022–2023), with several thousand respondents per country. For 21 countries, Cycle 1 data were collected in 2011–2012 (Austria, Belgium, Canada, Czechia, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, Poland, Slovakia, South Korea, Spain, Sweden, the United Kingdom, and the United States), for five in 2014–2015 (Chile,

Israel, Lithuania, New Zealand, and Singapore), and for one in 2017–2018 (Hungary). Cycle 2 data were collected in 2022–2023. The data were accessed through the OECD Remote Code Execution (RCE) service, as the scientific-use files for the second PIAAC cycle are not publicly available.

2.1. Greenness exposure

Following Vona et al. (2018), we measure occupational greenness using task data from the O*NET Green Task Development Project (Dierdorff et al., 2009), which classifies the specific tasks of occupations affected by the greening of the economy as green or non-green. The greenness of occupation k is the share of green specific tasks in all specific tasks:

$$Greenness_k = \frac{\# \text{ green specific tasks}_k}{\# \text{ total specific tasks}_k}$$

The index ranges from 0 (no green tasks) to 1 (all specific tasks green), which distinguishes core green occupations, such as environmental engineers, from those that combine a few green tasks with conventional ones. As in Vona et al. (2018), the index is computed for eight-digit O*NET-SOC occupations, averaged to six-digit SOC occupations, and aggregated further using US employment weights (BLS Occupational Employment Statistics). It is mapped to four-digit ISCO-08 occupations through the SOC–ISCO-08 crosswalk (Goos et al., 2014; Vona, 2021). Of the 422 four-digit ISCO-08 occupations, 100 have a positive score and 15 are entirely green. Because our sample consists mainly of advanced economies, imputing US task content to other countries is a reasonable approximation (Dicarlo et al., 2016).

Unlike the task-adjusted measures of AI exposure, RTI and social skills, greenness is defined at the occupation level: all workers in an occupation receive the same score regardless of country or survey cycle, so differences in greenness across countries and over time reflect only occupational composition. Greenness is assigned to PIAAC respondents at the four-digit ISCO level, the most detailed level available in PIAAC, and standardised to mean zero and unit variance within the estimation sample

2.2. Country classification by green patent stocks

We classify countries into three groups according to their green patent knowledge stocks per capita. Using green patent counts from PATSTAT, we construct country-level knowledge stocks following the perpetual inventory method of Verdolini and Galeotti (2011), assuming an annual depreciation rate of

10%. We use 2023 as the reference year and divide each country's stock by its population (in millions). We then rank the 27 countries in our sample according to their green patent stocks per capita and divide them into terciles. The nine countries with the highest stocks are classified as Leaders: Japan, Germany, Korea, the Netherlands, Sweden, Denmark, Finland, Austria, and Norway. The middle nine are classified as Adopters: the United States, France, the United Kingdom, Italy, Canada, Belgium, Israel, Ireland, and Singapore. The bottom nine are classified as Laggards: Spain, Poland, New Zealand, Czechia, Hungary, Chile, the Slovak Republic, Estonia, and Lithuania. All classification thresholds are determined within our 27-country sample.

2.3. AI exposure

Following Lewandowski et al. (2025), we construct a worker-level measure of AI exposure based on PIAAC work-related questions and the AI Occupational Exposure (AIOE) index of Felten et al. (2021). Unlike occupation-level measures that assign the same exposure to all workers in a given occupation, task-adjusted measure captures cross-country and within-occupation differences in job tasks and skill use at work. It therefore allows differences in AI exposure to reflect not only shifts in occupational composition, but also changes in the task content of jobs. Task-adjusted AI exposure (AIE_{io}) is calculated as:

$$AIE_{io} = \frac{1}{Y_o} \sum_{j=1}^{35} A_j \left(\sum_n \hat{\beta}_{jn} Q_i^n \right) \quad (2)$$

where A_j is the AI exposure score of ability j from Felten et al., (2021), and Y_o is the number of relevant abilities in occupation o , $Q_{i,o}^n$ represents responses to PIAAC question n by worker i in occupation o , and $\hat{\beta}_{jn}$ is estimated weight linking question n to ability j . For methodological details, see Lewandowski et al. (2025). AI exposure is standardised to mean zero and unit variance within the estimation sample.

2.4. RTI

Following Lewandowski et al. (2022), we construct a worker-level measure of routine task intensity (RTI) in the spirit of Acemoglu and Autor (2011). We exclude farmers and skilled agricultural workers (ISCO 6) from the sample. For further methodological details, see Lewandowski et al. (2022). Worker-level RTI is calculated as:

$$RTI = \ln(r_{cog}) - \frac{(nr_{analytical} + nr_{personal})}{2} \quad (1)$$

where, r_{cog} , $nr_{analytical}$, $nr_{personal}$ are routine cognitive, non-routine cognitive analytical, and non-routine cognitive personal task levels. RTI is standardised to mean zero and unit variance within the estimation sample.

2.5. Social Skill Index

To measure the social skill intensity, we follow Lewandowski & Madoń (2026) and construct a worker-level Social Skills Index (SSI) based on PIAAC work-related task measures. The SSI builds on the social-skill measure developed by Deming (2017)) which is based on four interpersonal ONET abilities characterising occupations in the United States: social perceptiveness, coordination, negotiation, and persuasion. We calibrate the mapping between PIAAC task measures and the ONET social-skill components using the U.S. PIAAC Cycle 1 sample and apply the estimated coefficients to country-specific PIAAC task measures. This allows the task content of the same occupation to vary across countries while keeping the definition of social skills fixed. For methodological details, see Lewandowski & Madoń (2026). SSI is standardised to mean zero and unit variance within the estimation sample.

3. Econometric approach

We estimate the relationship between the task and skill content of jobs and occupational greenness, and examine whether this relationship differs across countries at different stages of green-technology adoption and between the two survey waves. Because greenness is defined at the occupation level, while task and skill measures vary across workers, we use each measure as the dependent variable and greenness as the key regressor.

The outcomes are three worker-level measures: AI exposure, routine task intensity (RTI), and the Social Skill Index (SSI). The main regressor of interest is O*NET occupational greenness. All four measures are standardised to mean zero and unit variance in the employment-weighted estimation sample, so the coefficients are expressed in standard-deviation units. Human-capital controls (HC_{icost}) include literacy and numeracy proficiency-level dummies (level 2 as the reference category), age-group dummies, education dummies, and a gender dummy.

For each outcome I_{icost} (standardised AI exposure, RTI, or SSI), we estimate:

$$I_{icost} = \beta_1 GRN_o + \beta_2 HC_{icost} + \beta_3 \delta_t + \mu_c + \phi_o + \psi_s + \epsilon_{icost} \quad (1)$$

for worker i in country c , occupation o , sector s , and period t . GRN_o denotes standardised occupational greenness, δ_t is an indicator for the second PIAAC cycle (2022–2023), and μ_c , ϕ_o , and ψ_s denote

country, occupation (ISCO 2-digit), and sector (NACE 1-digit) fixed effects, respectively. The coefficient β_1 captures the association between occupational greenness and skill measure, conditional on worker characteristics and the included fixed effects. Notably, since greenness varies only across occupations, β_1 is identified from differences between occupations; once 2-digit ISCO fixed effects are included, only differences between 3-digit occupations within the same 2-digit group remain.

To test whether the relationship between occupational greenness and skill content varies with a country's position in green innovation, we interact greenness with Green-Patent Group indicators, GPG_c^g : Leader and Adopter, with Laggard as the reference category. Countries are classified into Leaders, Adopters and Laggards according to terciles of population-weighted green patents (PATSTAT, Y02 tag) per capita in 2012, i.e. before the analysis period. Specifically:

$$I_{icos} = \beta_1 GRN_o + \sum_{g \in \{L,A\}} \lambda_g (GRN_o \times GPG_c^g) + \beta_2 HC_{icos} + \beta_3 \delta_t + \mu_c + \phi_o + \psi_s + \epsilon_{icost} \quad (2)$$

The interaction coefficients λ_g capture differences in the slope of the relationship between occupational greenness and the outcome variable for Leader and Adopter countries relative to Laggards. Finally, To test whether the greenness–skill relationship changed between 2011-2018 (PIAAC cycle 1) and 2022-2023 (PIAAC cycle2), we interact greenness with the cycle-2 indicator:

$$I_{icos} = \beta_1 GRN_o + \beta_2 \delta_t + \tau (GRN_o \times \delta_t) + \beta_2 HC_{icos} + \mu_c + \phi_o + \psi_s + \epsilon_{icost} \quad (3)$$

where δ_t indicates the second PIAAC cycle (2022–2023), which we further refer to as the time trend. Since all countries in the balanced sample are observed in both waves, δ_t varies within countries and is not absorbed by the country fixed effects. The coefficient β_2 captures the greenness gradient in the 2011-2018 (PIAAC 1st cycle), while τ captures the change in this gradient between 2011-2018 and 2022-2023 (PIAAC 2nd cycle); $\beta + \tau$ gives the corresponding gradient in the 2022-2023 (PIAAC 2nd cycle). The coefficient δ_t captures the average between-cycle difference in the outcome I_{icos} at mean greenness. As occupational greenness is time-invariant, τ does not capture changes in greenness, but whether the outcome evolved differently in greener than in less green occupations between the two cycles.

4. Descriptive evidence

AI exposure increases over time, both overall and within all country groups (Table 1). This reflects changes in occupational structure as well as increases in AI exposure within occupations, with the latter being the dominant channel. AI exposure is consistently highest among Leaders, followed by Adopters

and Laggards. This suggests that countries more advanced in green innovation also tend to be more exposed to AI.

The pattern for occupational greenness is less pronounced. Changes over time are very small, which is expected because the O*NET greenness measure is fixed at the occupation level and therefore changes only through shifts in occupational composition.

Greenness¹ is highest among Laggards, followed by Leaders and Adopters (Table 1). This appears to be partly related to the occupational structure of employment. Laggard countries have a higher share of non-routine manual (NRM) occupations, and the composition of NRM employment may also be tilted towards relatively greener jobs. Examples of particularly green NRM occupations include Electrical Equipment Installers and Repairers (ISCO 741), Locomotive Engine Drivers and Related Workers (ISCO 831), Heavy Truck and Bus Drivers (ISCO 833), and Refuse Workers (ISCO 961).

Leaders are greener than Adopters mainly because their non-routine manual, non-routine cognitive analytical and routine manual occupations are greener (Table 2). Because greenness is imputed from US task content, it captures cross-country differences in occupational structure, not differences in how green the same occupation is across countries. The higher greenness of Laggards therefore does not indicate more advanced green technology adoption.

Table 1. Evolution of greenness and AI exposure, countries covered in PIAAC cycles

		Overall	Laggards	Adopters	Leaders
AI exposure (standardised)	PIAAC 1	-0.081	-0.219	-0.064	0.04
	PIAAC 2	0.081	-0.021	0.086	0.177
Greenness (O*NET, standardised)	PIAAC 1	-0.001	0.047	-0.057	0.008
	PIAAC 2	0.001	0.047	-0.05	0.004
Greenness (O*NET, raw)	PIAAC 1	0.047	0.054	0.039	0.048
	PIAAC 2	0.047	0.054	0.04	0.048

Note: Leaders: JP, DE, KR, NL, SE, DK, FI, AT, NO. Adopters: US, FR, UK, IT, CA, BE, IL, IE, SG. Laggards: ES, PL, NZ, CZ, HU, CL, SK, EE, LT.

Table 2. Task groups employment shares and greenness (O*NET) in 2012-2018 (PIAAC 1 cycle)

	Laggards		Adopters		Leaders	
	Employment Share	Greenness (O*NET)	Employment Share	Greenness (O*NET)	Employment Share	Greenness (O*NET)
NRCA	16%	0.107	20%	0.067	20%	0.144
NRCP	15%	-0.047	19%	-0.020	14%	-0.111
NRM	30%	0.443	26%	0.116	28%	0.297
RC	24%	-0.286	27%	-0.303	28%	-0.306

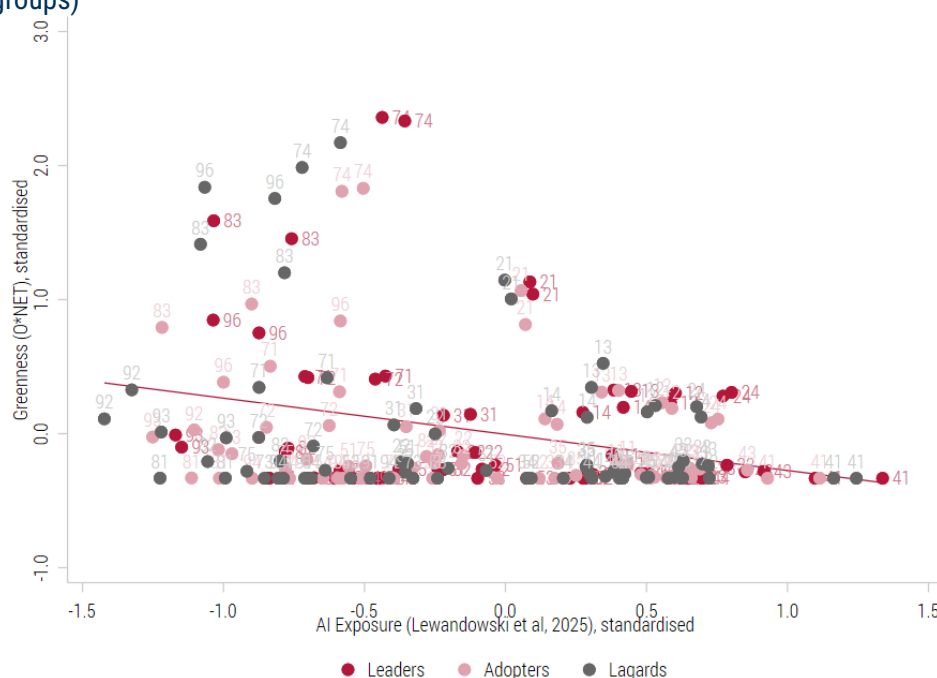
¹ We report greenness both in its raw and standardised form. The standardised measure corresponds to the specification used in the regression analysis and facilitates interpretation of the estimated coefficients in standard-deviation units. The raw measure is reported to preserve the original scale of the indicator and provide a more intuitive indication of differences in the level of occupational greenness across country groups.

RM	14%	-0.204	8%	-0.176	10%	-0.011
----	-----	--------	----	--------	-----	--------

Note: NRCA-Non-routine Cognitive Analytical; NRCP- Non-routine Cognitive Personal; NRM- Non-routine Manual; RC- Routine Cognitive; RM- Routine Manual. See Table A1 for allocation of occupations to task groups.

Figure 1 shows that greenness and AI exposure are negatively correlated across two-digit occupations. Within country groups, the correlation ranges from -0.28 among Adopters to -0.36 among Leaders, while the pooled correlation is -0.33 . This relationship is largely driven by three manual occupational groups with high greenness and low AI exposure: electrical and electronic trades workers (ISCO 74), drivers and mobile plant operators (ISCO 83), and refuse workers and other elementary workers (ISCO 96). Excluding these groups weakens the pooled correlation to -0.12 , indicating that they account for much of the negative association.

Figure 1 Correlation between greenness and AI exposure across 2-digit ISCO occupations (labels indicate occupational groups)



Note: Own elaboration based on PIAAC, O*NET and Lewandowski et al. (2025) data.

5. Econometric evidence

We estimate Equation (1) separately for AI exposure, RTI and the SSI. Table 3 reports OLS estimates of the greenness coefficient: column (1) includes country fixed effects, column (2) adds 2-digit ISCO fixed effects, and column (3) further adds 1-digit NACE fixed effects. Tables 4 and 5 report the estimates of Equations (3) and (2), which allow the greenness gradient to differ between survey cycles and across country groups.

Occupational greenness is negatively associated with AI exposure (Table 3, Panel A). Conditional on country fixed effects and human capital, a one-standard-deviation increase in greenness is associated with 0.10 SD lower AI exposure. The coefficient falls by over 90% once 2-digit ISCO fixed effects are included, but remains negative and significant, and sector fixed effects leave it unchanged. The association therefore arises mostly between broad occupational groups: green jobs are concentrated in manual occupations, such as electrical trades, drivers and refuse workers, which are among the least exposed to AI (Section 4). Within 2-digit groups, greener occupations are only slightly less exposed. For RTI and the SSI, greenness shows small associations (positive for RTI, negative for the SSI) that disappear once occupation fixed effects are included (Panels B and C).

The results reveal a distinction between AI exposure and the SSI. The negative association between greenness and the SSI characterises differences between broad occupational groups: greener occupations are, on average, less intensive in social tasks, but this relationship disappears within two-digit occupational groups. In contrast, greener occupations are not only less exposed to AI on average. The negative association remains after accounting for broad occupational and sectoral differences, indicating that workers in greener four-digit occupations perform slightly less AI-exposed tasks. However, the small magnitude of the coefficient shows that most of the greenness–AI relationship also operates between broad occupational groups.

Table 3. Greenness as correlate of task-based skill measures: OLS estimations

Variable	(1)	(2)	(3)
Panel A: AI exposure			
Greenness (ONET)	-0.100*** (0.007)	-0.008*** (0.003)	-0.010*** (0.003)
Panel B: RTI			
Greenness (ONET)	0.017*** (0.006)	0.003 (0.004)	0.002 (0.004)
Panel C: Social Skill Index			
Greenness (ONET)	-0.030*** (0.008)	-0.001 (0.002)	-0.001 (0.002)
Country FE	Yes	Yes	Yes
ISCO 2d FE	No	Yes	Yes
NACE 1d FE	No	No	Yes
Observations	222481	222481	218514

Note: Base categories – Men, Secondary education, aged 35-44, Lower-medium literacy proficiency (level 2). Standard errors in parentheses. See Table A1 in Appendix for full estimation results. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Own estimates based on PIAAC, O*NET, Lewandowski & Madoń (2026), Lewandowski et al. (2022) and Lewandowski et al. (2025) data.

The negative association between greenness and AI exposure weakened between the two PIAAC cycles (Table 4, Panel A). The positive interaction reduces the 2011–2018 gradient by about a fifth in 2022–2023, and within 2-digit occupations the gradient almost disappears in the second cycle. As greenness is fixed at the occupation level, this means that AI exposure rose more in greener occupations than in less green ones. The negative greenness gradient of the SSI roughly halves between cycles, although this is only marginally significant within occupations. The relationship between greenness and RTI does not change over time.

The negative greenness–AI gradient is about 50% steeper in Leader countries than in Laggards, while Adopters do not differ from Laggards (Table 5, Panel A). For RTI and the SSI, the interactions offset the main effects in Adopter countries, where the gradients are close to zero. None of the interactions survives the inclusion of 2-digit ISCO fixed effects. Differences across country groups therefore reflect how green and AI-exposed jobs are distributed across broad occupational groups, rather than differences within occupations. We find no evidence that countries with different accumulated green patent knowledge stocks exhibit systematically different within-occupation relationships between occupational greenness and AI exposure, routine task intensity or social skill use. Thus, green innovation intensity, as captured by green patent stocks per capita, is not associated with a distinct alignment between green tasks and AI-exposed task profiles within broad occupational groups. The differences observed before occupation fixed effects are included instead reflect differences in occupational structure across country groups.

Overall, green jobs and AI-exposed jobs overlap little, so the two transitions tend to affect different parts of the occupational distribution. This overlap has grown slightly over time and, once occupational structure is accounted for, is not systematically related to countries' position in green innovation.

Table 4. Greenness as correlate of skill measures (OLS estimations), by survey cycles

Variable	(1)	(2)	(3)
Panel A: AI exposure			
Greenness (ONET)	-0.110*** (0.009)	-0.013*** (0.004)	-0.015*** (0.004)
Greenness (ONET) × Time trend	0.021*** (0.007)	0.010** (0.005)	0.010** (0.005)
Time trend	0.136*** (0.021)	0.134*** (0.017)	0.136*** (0.017)
Panel B: RTI			
Greenness (ONET)	0.021*** (0.007)	0.004 (0.005)	0.003 (0.005)
Greenness (ONET) × Time trend	-0.007	-0.002	-0.002

	(0.005)	(0.005)	(0.005)
Time trend	-0.083***	-0.068***	-0.070***
	(0.018)	(0.017)	(0.017)
Panel C: Social Skill Index			
Greenness (ONET)	-0.041***	-0.006	-0.006
	(0.011)	(0.004)	(0.004)
Greenness (ONET) × Time trend	0.022***	0.009	0.010*
	(0.008)	(0.006)	(0.006)
Time trend	0.578***	0.561***	0.561***
	(0.036)	(0.037)	(0.037)
Country FE	Yes	Yes	Yes
ISCO 2d FE	No	Yes	Yes
NACE 1d FE	No	No	Yes
Observations	222481	222481	218514

Table 5. Greenness as correlate of skill measures (OLS estimations), by country groups

Variable	(1)	(2)	(3)
Panel A: AI exposure			
Greenness (ONET)	-0.088***	-0.011**	-0.013***
	(0.006)	(0.005)	(0.005)
Leader × Greenness	-0.044**	0.003	0.003
	(0.019)	(0.007)	(0.007)
Adopter × Greenness	0.000	0.009	0.008
	(0.008)	(0.008)	(0.007)
Panel B: RTI			
Greenness (ONET)	0.026***	0.005	0.004
	(0.007)	(0.006)	(0.006)
Leader × Greenness	-0.000	0.001	0.002
	(0.016)	(0.010)	(0.009)
Adopter × Greenness	-0.031***	-0.011	-0.010
	(0.009)	(0.007)	(0.007)
Panel C: Social Skill Index			
Greenness (ONET)	-0.040***	-0.002	-0.002
	(0.010)	(0.003)	(0.003)
Leader × Greenness	-0.006	-0.005	-0.004
	(0.024)	(0.011)	(0.011)
Adopter × Greenness	0.042**	0.009	0.009
	(0.017)	(0.008)	(0.008)
Country FE	Yes	Yes	Yes
ISCO 2d FE	No	Yes	Yes
NACE 1d FE	No	No	Yes
Observations	222481	222481	218514

Note: Leaders: JP, DE, KR, NL, SE, DK, FI, AT, NO. Adopters: US, FR, UK, IT, CA, BE, IL, IE, SG. Laggards: ES, PL, NZ, CZ, HU, CL, SK, EE, LT. Base categories – Men, Secondary education, aged 35-44, Lower-medium literacy proficiency (level 2). See Table A2 in Appendix for full estimation results. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Own estimates based on PIAAC, O*NET, Lewandowski & Madoń (2026), Lewandowski et al. (2022) and Lewandowski et al. (2025) data.

6. Conclusions

This report examined whether the green transition and the diffusion of AI affect the same workers. We related occupational greenness to worker-level, task-based measures of AI exposure, routine task intensity and social skills in 27 countries observed in two PIAAC cycles.

Our results show that the green and digital transitions currently have distinct occupational profiles. Greener occupations are, on average, less exposed to AI. This negative association arises mainly between broad occupational groups. Green tasks are concentrated in manual, technical and operational occupations, including electrical trades, driving and refuse collection. These jobs typically involve installing, operating or maintaining technologies and physical systems, and their tasks are among the least exposed to AI. By contrast, AI exposure is highest among occupations requiring cognitive and information-processing tasks, including clerical, professional and managerial work. The two transitions therefore currently affect different parts of the occupational and skill distribution.

These differences are not entirely explained by the division between broad occupational groups. Within two-digit occupational groups, workers in greener occupations remain slightly less exposed to AI, although the association is small. This suggests that even among broadly similar occupations, greener jobs contain somewhat fewer AI-exposed tasks. However, greenness is not robustly related to routine task intensity. Greener occupations also use social skills slightly less intensively on average, but this difference disappears within two-digit occupational groups. Social-skill use therefore distinguishes broad types of occupations rather than greener and less-green jobs within the same occupational group. The results do not identify either routine intensity or social skills as defining dimensions of green work, although they do not show whether these skills could facilitate future worker mobility.

The relationship between greenness and AI exposure also varies over time and across countries. The negative association weakened between 2011–2018 and 2022–2023 because AI exposure increased relatively more in greener occupations. It is also steeper in Leader countries than in Laggards, but this difference disappears within broad occupational groups. Differences across country groups thus reflect their occupational structures rather than systematically different task profiles within occupations.

Our findings have direct implications for skills policy. Policies supporting workers through the two transitions are therefore likely to reach different groups with different skill profiles: manual and technical workers in green occupations on the one hand, and workers in more AI-exposed, cognitive occupations on the other. At the same time, the weakening of the negative association suggests that AI

is gradually reaching greener occupations, so the overlap between the two transitions may grow over time, potentially increasing the need for AI-related upskilling among workers in green occupations.

Our analysis has some limitations. Greenness is measured at the occupation level and imputed from US task data, so it captures differences in occupational structure, but not differences in how green the same occupation is across countries or over time. Moreover, our estimates are conditional associations rather than causal effects. Measures of greenness that vary across countries and over time would allow future work to assess whether the greening of jobs within occupations relates to AI exposure in the same way.

References

- Acemoglu, D., & Autor, D. (2011). 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)
- Consoli, D., Marin, G., Marzucchi, 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.
- Deming, D. J. (2017). The Growing Importance of Social Skills in the Labor Market*. *The Quarterly Journal of Economics*, 132(4), 1593–1640. <https://doi.org/10.1093/qje/qjx022>
- Dicarlo, E., Lo Bello, S., Monroy-Taborda, S., Oviedo, A. M., Sanchez Puerta, M. L., & Santos, I. (2016). *The skill content of occupations across low and middle income countries: Evidence from harmonized data* (IZA Discussion Paper No. 10224). IZA – Institute of Labor Economics.
- Dierdorff, E. C., Norton, J. J., Drewes, D. W., Kroustalis, C. M., Rivkin, D., & Lewis, P. (2009). *Greening of the world of work: Implications for O*NET-SOC and new and emerging occupations*. National Center for O*NET Development.
- 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>

- Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8), 2509–2526.
- Lewandowski, P., & Madoń, K. (2026). *Drivers of skill use at work (SkilMeet Deliverable 4.1)* (Grant agreement no. 101132581). SkilMeet.
- Lewandowski, P., Madoń, K., & Park, A. (2025). Workers' AI Exposure Across Development Levels. *IZA – Institute of Labor Economics, IZA Discussion Paper Series*, 18235.
- Lewandowski, P., Park, A., Hardy, W., Du, Y., & Wu, S. (2022). Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data. *World Bank Economic Review*, 36(3), 687–708. <https://doi.org/10.1093/wber/lhac005>
- Verdolini, E., & Galeotti, M. (2011). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of Environmental Economics and Management*, 61(2), 119–134. <https://doi.org/10.1016/j.jeem.2010.08.004>
- Vona, F. (2021). *Labour markets and the green transition: A practitioner's guide to the task-based approach* (JRC Technical Report JRC126681). 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>

Appendix

Table A1. Task Group Allocation, by Occupation (ISCO08 2-digit)

ISCO08 code	Task Group	Title
11	NRC	Chief Executives, Senior Officials and Legislators
12	NRC	Administrative and Commercial Managers
13	NRC	Production and Specialized Services Managers
14	NRC	Hospitality, Retail and Other Services Managers
21	NRC	Science and Engineering Professionals
22	NRC	Health Professionals
23	NRC	Teaching Professionals
24	NRC	Business and Administration Professionals
25	NRC	Information and Communications Technology Professionals
26	NRC	Legal, Social and Cultural Professionals
31	NRC	Science and Engineering Associate Professionals
32	NRC	Health Associate Professionals
33	RC	Business and Administration Associate Professionals
34	RC	Legal, Social, Cultural and Related Associate Professionals
35	NRC	Information and Communications Technicians
41	RC	General and Keyboard Clerks
42	RC	Customer Services Clerks
43	RC	Numerical and Material Recording Clerks
44	RC	Other Clerical Support Workers
51	NRM	Personal Services Workers
52	RC	Sales Workers
53	NRM	Personal Care Workers
54	NRM	Protective Services Workers
61	NRM	Market-oriented Skilled Agricultural Workers
62	NRM	Market-oriented Skilled Forestry, Fishery and Hunting Workers
63	NRM	Subsistence Farmers, Fishers, Hunters and Gatherers
71	NRM	Building and Related Trades Workers (excluding Electricians)
72	RM	Metal, Machinery and Related Trades Workers
73	RM	Handicraft and Printing Workers
74	NRM	Electrical and Electronic Trades Workers
75	RM	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers
81	RM	Stationary Plant and Machine Operators
82	RM	Assemblers
83	NRM	Drivers and Mobile Plant Operators
91	NRM	Cleaners and Helpers
92	NRM	Agricultural, Forestry and Fishery Labourers
93	NRM	Labourers in Mining, Construction, Manufacturing and Transport
94	RM	Food Preparation Assistants
95	NRM	Street and Related Sales and Services Workers
96	NRM	Refuse Workers and Other Elementary Workers

Source: own elaboration based on Acemoglu and Autor (2011)

Note: NRC – Nonroutine Cognitive, RC – Routine Cognitive, RM – Routine Manual, NRM – Nonroutine Manual.

Table A2 Correlation between greenness and AI exposure, RTI and Social Skill Index: full estimation results

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Greenness (ONET)	-0.100*** (0.007)	-0.008*** (0.003)	-0.010*** (0.003)	0.017*** (0.006)	0.003 (0.004)	0.002 (0.004)	-0.030*** (0.008)	-0.001 (0.002)	-0.001 (0.002)
Literacy Level 1	-0.174*** (0.023)	-0.096*** (0.016)	-0.091*** (0.016)	0.109*** (0.024)	0.042** (0.018)	0.041** (0.018)	-0.156*** (0.022)	-0.013 (0.008)	-0.012 (0.009)
Literacy Level 3	0.109*** (0.015)	0.050*** (0.011)	0.048*** (0.011)	-0.081*** (0.012)	-0.033*** (0.009)	-0.030*** (0.009)	0.103*** (0.016)	0.010 (0.008)	0.009 (0.008)
Literacy Level 4	0.112*** (0.023)	0.036** (0.017)	0.032* (0.017)	-0.122*** (0.027)	-0.047** (0.019)	-0.039** (0.019)	0.122*** (0.026)	-0.006 (0.013)	-0.006 (0.013)
Numeracy Level 1	-0.194*** (0.017)	-0.134*** (0.015)	-0.135*** (0.015)	0.101*** (0.012)	0.042*** (0.012)	0.043*** (0.013)	-0.168*** (0.015)	-0.019*** (0.005)	-0.018*** (0.005)
Numeracy Level 3	0.112*** (0.016)	0.066*** (0.011)	0.067*** (0.012)	-0.126*** (0.012)	-0.058*** (0.010)	-0.058*** (0.010)	0.137*** (0.013)	0.010** (0.004)	0.011*** (0.004)
Numeracy Level 4	0.165*** (0.030)	0.070*** (0.021)	0.072*** (0.021)	-0.263*** (0.022)	-0.106*** (0.016)	-0.105*** (0.016)	0.273*** (0.022)	0.015* (0.009)	0.016* (0.009)
Education: Primary	-0.408*** (0.024)	-0.267*** (0.018)	-0.259*** (0.018)	0.277*** (0.019)	0.151*** (0.014)	0.148*** (0.015)	-0.323*** (0.029)	-0.023*** (0.007)	-0.021*** (0.007)
Education: Tertiary	0.382*** (0.039)	0.191*** (0.021)	0.183*** (0.021)	-0.538*** (0.028)	-0.202*** (0.017)	-0.198*** (0.017)	0.616*** (0.036)	0.022*** (0.006)	0.022*** (0.006)
Age: <25	-0.392*** (0.040)	-0.386*** (0.036)	-0.365*** (0.035)	0.343*** (0.031)	0.249*** (0.025)	0.244*** (0.025)	-0.155*** (0.031)	-0.010 (0.008)	-0.008 (0.008)
Age: 25-34	-0.044*** (0.012)	-0.035*** (0.010)	-0.031*** (0.010)	0.069*** (0.011)	0.045*** (0.011)	0.043*** (0.011)	-0.036*** (0.009)	0.005 (0.004)	0.005 (0.004)
Age: 45-54	-0.033** (0.013)	-0.036*** (0.009)	-0.036*** (0.009)	0.010 (0.013)	0.017* (0.009)	0.019** (0.009)	0.003 (0.009)	-0.010*** (0.004)	-0.010*** (0.004)
Age: 55+	-0.078*** (0.023)	-0.102*** (0.015)	-0.104*** (0.015)	0.060*** (0.021)	0.076*** (0.014)	0.079*** (0.014)	0.025 (0.020)	-0.010 (0.008)	-0.010 (0.008)
Gender: Women	0.122*** (0.018)	-0.150*** (0.012)	-0.152*** (0.012)	0.165*** (0.016)	0.175*** (0.014)	0.177*** (0.015)	0.059*** (0.021)	-0.017*** (0.005)	-0.015*** (0.005)
Time Trend	0.136*** (0.021)	0.134*** (0.017)	0.136*** (0.017)	-0.083*** (0.018)	-0.068*** (0.017)	-0.070*** (0.017)	0.578*** (0.036)	0.561*** (0.037)	0.561*** (0.037)
Constant	-0.172*** (0.033)	0.380*** (0.032)	0.319*** (0.034)	0.091*** (0.024)	0.182*** (0.023)	0.264*** (0.028)	-0.619*** (0.027)	-0.446*** (0.048)	-0.476*** (0.046)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISCO 2d FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
NACE 1d FE	No	No	Yes	No	No	Yes	No	No	Yes
Observation	222481	222481	218514	220637	220637	216784	222481	222481	218514

Note: dependent variable in columns (1)-(3) is AI exposure, (4)-(6) RTI and (7)-(9) Social Skill Index. *Base categories – Men, Secondary education, aged 35-44, Lower-medium literacy proficiency (level 2).* Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Own estimates based on PIAAC, O*NET, Lewandowski & Madoń (2026), Lewandowski et al. (2022) and Lewandowski et al. (2025) data.

Table A3 Correlation between greenness and AI exposure, RTI, and the Social Skill Index, by country group: full estimation results

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Greenness (ONET)	-0.088*** (0.006)	-0.011** (0.005)	-0.013*** (0.005)	0.026*** (0.007)	0.005 (0.006)	0.004 (0.006)	-0.040*** (0.010)	-0.002 (0.003)	-0.002 (0.003)
Leader	0.198*** (0.005)	0.083*** (0.006)	0.083*** (0.006)	-0.227*** (0.004)	-0.158*** (0.005)	-0.158*** (0.005)	0.490*** (0.004)	0.350*** (0.006)	0.349*** (0.006)
Adopter	0.266*** (0.011)	0.192*** (0.009)	0.194*** (0.009)	-0.252*** (0.009)	-0.185*** (0.007)	-0.186*** (0.008)	0.763*** (0.009)	0.613*** (0.008)	0.613*** (0.008)
Leader × Greenness	-0.044** (0.019)	0.003 (0.007)	0.003 (0.007)	-0.000 (0.016)	0.001 (0.010)	0.002 (0.009)	-0.006 (0.024)	-0.005 (0.011)	-0.004 (0.011)
Adopter × Greenness	0.000 (0.008)	0.009 (0.008)	0.008 (0.007)	-0.031*** (0.009)	-0.011 (0.007)	-0.010 (0.007)	0.042** (0.017)	0.009 (0.008)	0.009 (0.008)
Literacy level 1	-0.174*** (0.022)	-0.096*** (0.016)	-0.091*** (0.016)	0.109*** (0.024)	0.042** (0.018)	0.041** (0.018)	-0.156*** (0.022)	-0.013 (0.008)	-0.012 (0.009)
Literacy level 3	0.109*** (0.015)	0.050*** (0.011)	0.048*** (0.011)	-0.081*** (0.012)	-0.033*** (0.009)	-0.030*** (0.009)	0.103*** (0.016)	0.010 (0.008)	0.009 (0.008)
Literacy level 4	0.111*** (0.023)	0.036** (0.017)	0.032* (0.017)	-0.122*** (0.027)	-0.047** (0.019)	-0.039** (0.019)	0.122*** (0.026)	-0.006 (0.013)	-0.006 (0.013)
Numeracy level 1	-0.194*** (0.017)	-0.134*** (0.015)	-0.135*** (0.015)	0.101*** (0.012)	0.042*** (0.012)	0.043*** (0.013)	-0.168*** (0.015)	-0.019*** (0.005)	-0.018*** (0.005)
Numeracy level 3	0.112*** (0.016)	0.066*** (0.011)	0.067*** (0.012)	-0.126*** (0.012)	-0.058*** (0.010)	-0.058*** (0.010)	0.136*** (0.013)	0.010** (0.004)	0.011*** (0.004)
Numeracy level 4	0.166*** (0.030)	0.070*** (0.021)	0.072*** (0.021)	-0.263*** (0.022)	-0.106*** (0.016)	-0.105*** (0.016)	0.273*** (0.022)	0.015* (0.009)	0.016* (0.009)
Education: primary	-0.409*** (0.024)	-0.267*** (0.018)	-0.259*** (0.018)	0.277*** (0.019)	0.151*** (0.014)	0.148*** (0.015)	-0.323*** (0.029)	-0.024*** (0.007)	-0.021*** (0.007)
Education: tertiary	0.382*** (0.039)	0.191*** (0.021)	0.183*** (0.021)	-0.537*** (0.028)	-0.202*** (0.017)	-0.198*** (0.017)	0.616*** (0.036)	0.022*** (0.006)	0.022*** (0.006)
Age <25	-0.392*** (0.040)	-0.386*** (0.036)	-0.365*** (0.035)	0.343*** (0.031)	0.249*** (0.025)	0.244*** (0.025)	-0.154*** (0.031)	-0.010 (0.008)	-0.008 (0.008)
Age 25–34	-0.044*** (0.012)	-0.035*** (0.010)	-0.031*** (0.010)	0.069*** (0.011)	0.045*** (0.011)	0.043*** (0.011)	-0.036*** (0.009)	0.005 (0.004)	0.005 (0.004)
Age 45–54	-0.033** (0.013)	-0.036*** (0.009)	-0.036*** (0.009)	0.010 (0.013)	0.017* (0.009)	0.018** (0.009)	0.003 (0.009)	-0.010*** (0.004)	-0.010*** (0.004)
Age 55+	-0.078*** (0.023)	-0.101*** (0.015)	-0.104*** (0.015)	0.059*** (0.021)	0.076*** (0.014)	0.079*** (0.014)	0.025 (0.020)	-0.010 (0.008)	-0.010 (0.008)
Women	0.121*** (0.018)	-0.150*** (0.012)	-0.152*** (0.012)	0.165*** (0.016)	0.175*** (0.014)	0.177*** (0.015)	0.059*** (0.021)	-0.017*** (0.005)	-0.015*** (0.005)
Time trend	0.136*** (0.021)	0.134*** (0.017)	0.136*** (0.017)	-0.082*** (0.018)	-0.068*** (0.017)	-0.070*** (0.017)	0.578*** (0.036)	0.561*** (0.037)	0.561*** (0.037)
Constant	-0.367*** (0.029)	0.297*** (0.030)	0.235*** (0.033)	0.317*** (0.021)	0.340*** (0.021)	0.422*** (0.027)	-1.108*** (0.025)	-0.796*** (0.051)	-0.826*** (0.049)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISCO 2d FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
NACE 1d FE	No	No	Yes	No	No	Yes	No	No	Yes
Observation	213075	213075	209478	211286	211286	207799	213075	213075	209478

Note: *See notes to Table A1. Leaders: JP, DE, KR, NL, SE, DK, FI, AT, NO. Adopters: US, FR, UK, IT, CA, BE, IL, IE, SG. Laggards: ES, PL, NZ, CZ, HU, CL, SK, EE, LT*
Source: Own estimates based on PIAAC, O*NET, Lewandowski & Madoń (2026), Lewandowski et al. (2022) and Lewandowski et al. (2025) data.

Table A4 Correlation between greenness and AI exposure, RTI, and the Social Skill Index, by country survey cycle: full estimation results

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Greenness (ONET, std)	-0.110*** (0.009)	-0.013*** (0.004)	-0.015*** (0.004)	0.021*** (0.007)	0.004 (0.005)	0.003 (0.005)	-0.041*** (0.011)	-0.006 (0.004)	-0.006 (0.004)
Greenness × Time trend	0.021*** (0.007)	0.010** (0.005)	0.010** (0.005)	-0.007 (0.005)	-0.002 (0.005)	-0.002 (0.005)	0.022*** (0.008)	0.009 (0.006)	0.010* (0.006)
Time trend	0.136*** (0.021)	0.134*** (0.017)	0.136*** (0.017)	-0.083*** (0.018)	-0.068*** (0.017)	-0.070*** (0.017)	0.578*** (0.036)	0.561*** (0.037)	0.561*** (0.037)
Literacy level 1	-0.174*** (0.023)	-0.096*** (0.016)	-0.091*** (0.016)	0.109*** (0.024)	0.042** (0.018)	0.041** (0.018)	-0.156*** (0.022)	-0.013 (0.008)	-0.013 (0.009)
Literacy level 3	0.109*** (0.015)	0.050*** (0.011)	0.048*** (0.011)	-0.081*** (0.012)	-0.033*** (0.009)	-0.030*** (0.009)	0.103*** (0.016)	0.010 (0.008)	0.009 (0.008)
Literacy level 4	0.112*** (0.023)	0.036** (0.017)	0.032* (0.017)	-0.122*** (0.027)	-0.047** (0.019)	-0.039** (0.019)	0.122*** (0.026)	-0.005 (0.013)	-0.006 (0.013)
Numeracy level 1	-0.193*** (0.017)	-0.134*** (0.015)	-0.135*** (0.015)	0.101*** (0.012)	0.042*** (0.012)	0.043*** (0.013)	-0.168*** (0.015)	-0.019*** (0.005)	-0.018*** (0.005)
Numeracy level 3	0.112*** (0.016)	0.066*** (0.011)	0.067*** (0.012)	-0.126*** (0.012)	-0.058*** (0.010)	-0.058*** (0.010)	0.136*** (0.013)	0.010** (0.004)	0.011*** (0.004)
Numeracy level 4	0.164*** (0.030)	0.070*** (0.021)	0.072*** (0.021)	-0.263*** (0.022)	-0.106*** (0.016)	-0.105*** (0.016)	0.273*** (0.022)	0.015* (0.009)	0.016* (0.009)
Education: primary	-0.408*** (0.024)	-0.267*** (0.018)	-0.259*** (0.018)	0.277*** (0.019)	0.151*** (0.014)	0.148*** (0.015)	-0.323*** (0.029)	-0.023*** (0.007)	-0.021*** (0.007)
Education: tertiary	0.382*** (0.039)	0.191*** (0.021)	0.183*** (0.021)	-0.538*** (0.028)	-0.202*** (0.017)	-0.198*** (0.017)	0.616*** (0.036)	0.022*** (0.006)	0.022*** (0.006)
Age <25	-0.392*** (0.040)	-0.386*** (0.036)	-0.365*** (0.035)	0.343*** (0.031)	0.249*** (0.025)	0.244*** (0.025)	-0.155*** (0.031)	-0.010 (0.008)	-0.008 (0.008)
Age 25–34	-0.044*** (0.012)	-0.035*** (0.010)	-0.031*** (0.010)	0.069*** (0.011)	0.045*** (0.011)	0.043*** (0.011)	-0.037*** (0.009)	0.005 (0.004)	0.005 (0.004)
Age 45–54	-0.033** (0.013)	-0.036*** (0.009)	-0.036*** (0.009)	0.010 (0.013)	0.017* (0.009)	0.019** (0.009)	0.003 (0.009)	-0.010*** (0.004)	-0.010*** (0.004)
Age 55+	-0.078*** (0.023)	-0.102*** (0.015)	-0.104*** (0.015)	0.060*** (0.021)	0.077*** (0.014)	0.079*** (0.014)	0.025 (0.020)	-0.010 (0.008)	-0.010 (0.008)
Women	0.122*** (0.018)	-0.150*** (0.012)	-0.152*** (0.012)	0.165*** (0.016)	0.175*** (0.014)	0.177*** (0.015)	0.058*** (0.021)	-0.017*** (0.005)	-0.015*** (0.005)
Constant	-0.172*** (0.033)	0.380*** (0.032)	0.318*** (0.034)	0.090*** (0.024)	0.182*** (0.023)	0.264*** (0.028)	-0.619*** (0.027)	-0.446*** (0.048)	-0.477*** (0.046)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ISCO 2d FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
NACE 1d FE	No	No	Yes	No	No	Yes	No	No	Yes
Observation	213075	213075	209478	211286	211286	207799	213075	213075	209478

Note: See notes to Table A1. Leaders: JP, DE, KR, NL, SE, DK, FI, AT, NO. Adopters: US, FR, UK, IT, CA, BE, IL, IE, SG. Laggards: ES, PL, NZ, CZ, HU, CL, SK, EE, LT

Source: Own estimates based on PIAAC, O*NET, Lewandowski & Madoń (2026), Lewandowski et al. (2022) and Lewandowski et al. (2025) d



Skills for labour markets in the digital and green transition

SkiLMeeT is a research project carried out by eight research institutions, exploring how the digital and green transformation of European economies are changing the demand for skills. We analyse the scope of skills shortages and mismatches, identify their drivers and propose innovative ways to reduce skills gaps.

Follow us:

-  [linkedin.com/company/SkiLMeeT](https://www.linkedin.com/company/SkiLMeeT)
-  bsky.app/profile/skilmeet.bsky.social
-  twitter.com/SkiLMeeT
- www.skilmeet.eu



Funded by
the European Union

Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or European Research Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

SkiLMeeT Partners:

