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Abstract

This paper develops a task-adjusted, country-specific measure of workers' exposure to artificial intelligence (AI) across 103 countries, covering approximately 86% of global employment. Building on the AI Occupational Exposure index by Felten et al. (2021), we map AI-related abilities to worker-level tasks using survey data from PIAAC, STEP, and CULS. We then predict occupational AI exposure in countries lacking survey data using a regression-based approach. Our findings show that accounting for within-occupation task differences significantly amplifies the development gradient in AI exposure. About 47% of cross-country variation is explained by differences in task content, particularly among high-skilled occupations. We attribute these differences primarily to cross-country differences in ICT use intensity, followed by human capital and globalisation-related firm characteristic. We also document rising AI exposure over the past decade, driven largely by changes in task composition. Our results highlight the central role of digital infrastructure and skill use in shaping global AI exposure.

Keywords: job tasks, occupations, AI, technology, skills

JEL: J21, J23, J24

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1. Introduction

The rapid progress of large language models (LLMs) and generative AI (GenAI) has attracted significant public attention, particularly due to concerns about potential labour displacement. Empirical analysis of GenAI's labour market effects, however, has been limited by the scarcity of systematic data on AI investment and application. In response, researchers have turned to measuring workers' exposure to AI, typically combining patent data with occupational task information (Felten et al., 2021, 2018; Gmyrek et al., 2023; Webb, 2020). Most of this work focuses on the United States, leveraging detailed occupation-level data from the Occupational Information Network (O*NET). Yet, occupational tasks differ significantly across countries due to variation in technology use, skill supply, and participation in global value chains (Caunedo et al., 2023; Lewandowski et al., 2022). A key question is whether AI exposure varies across development levels and what factors drive these differences.

This paper provides a reliable measure of Artificial Intelligence (AI) exposure that accounts for task differences across countries at different development levels. We build upon the task approach to studying the interplay between technology and labour (Acemoglu and Autor, 2011; Autor, 2013). To measure the relationship between job tasks and exposure to AI, we combine the well-established Artificial Intelligence Occupational Exposure (AIOE) of Felten et al. (2021) with the worker-level survey data from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), World Bank's Skills towards Employment Programme (STEP), and China Urban Labor Survey (CULS) which jointly cover 50 countries across all development levels. First, we identify PIAAC survey questions that best map AI capabilities to U.S. occupations. Next, we apply the same question sets to compute AI exposure in other countries included in the STEP, PIAAC, and CULS surveys. Finally, we use regression models to examine factors associated with cross-country variation in AI exposure—particularly within similar occupations—and to predict occupational exposure in countries lacking survey data. In total, we estimate occupational AI exposure for 103 countries, representing approximately 86% of global employment, enabling cross-country comparisons across the development spectrum.

This study makes four main contributions. First, we generate country-specific AI exposure measures that reflect differences in tasks across a broad set of economies. Our regression-based method links O*NET ability requirements to PIAAC-reported job tasks, adapting the AIOE index to U.S. worker-level data and extending it globally. While prior work measured AI exposure using occupational tasks (Gmyrek et al., 2023; Webb, 2020), abilities (Felten et al., 2021, 2018), or AI-human complementarity (Pizzinelli et al., 2023), these studies generally produced occupation-level estimates uniform across countries. Gmyrek et al. (2024) adjusted exposure by computer access in Latin America, but, to our knowledge, this is the first study to rely on country-specific data on job tasks and skill use to produce internationally comparable, task-based measures of AI exposure.

Second, we document substantial heterogeneity in AI exposure across countries and occupations. Workers' AI exposure increases strongly with development level, both overall and within occupations. Decomposing cross-country variation, we find that differences in tasks explain approximately 47% of the observed variance, with remaining variation attributable to differences in occupational structures. Adjusting for task variation within occupations significantly amplifies cross-country disparities, especially in low- and middle-income countries and within high-skilled occupations such as managers, professionals, and technicians. Using two waves of PIAAC data for high-income countries, we also show that AI exposure has risen since the early 2010s, primarily due to changes in within-occupation task structures, underscoring the need to account for task content in exposure estimates.

Third, we identify key worker-level correlates of AI exposure. Greater ICT intensity at the country-sector level is positively associated with exposure, while higher integration in the globalised economy—measured by forward linkages in global value chains and FDI inflows—is negatively associated. Our use of workers' cognitive skill measures, such as literacy proficiency, enables us to account for international variation in education quality. We find that both education and cognitive skills are positively correlated with AI exposure. This has important distributional implications: if AI substitutes for skilled labour, it could reduce inequality; if it complements skilled labour, inequality may increase. Existing research often compares socio-economic groups based only on occupational composition, overlooking task-level variation and differences in actual skill levels (Cazzaniga et al., 2024; Comunale and Manera, 2024; Pizzinelli et al., 2023).

We further decompose cross-country exposure differences using our regression results and find that ICT intensity accounts for 50–64% of the variance. Occupational composition (15%), human capital (11%), and firm-level characteristics (3–20%) play smaller roles. Using various measures of ICT infrastructure, we confirm that digital usage and capabilities are key drivers of cross-country variation in AI exposure.

Fourth, we extend our estimates to 53 additional countries lacking survey data. Estimating occupation-specific regressions for countries with survey data, we predict occupational AI exposure values at the 1- and 2-digit ISCO08 levels based on countries' endowments. This expands our coverage to 103 countries, encompassing roughly 86% of global employment. Our results show that the top quartile of AI-exposed workers is concentrated in high-income countries, while the bottom quartile is concentrated in low- and middle-income countries. These findings challenge narratives of uniform global AI impact and suggest that high-income countries are likely to experience the greatest short-term effects.

This paper is structured as follows. Section 2 introduces the data, measurements, and methodology. Section 3 presents our results and stylised facts on global disparities in workers' AI exposure. Section 4 concludes.

2. Data and AI exposure measurement

2.1. Data for measurement of AI exposure

To construct worker-level measures of AI exposure, we combine data from the O*NET occupational abilities database with U.S. data from the OECD's Programme for the International Assessment of Adult Competencies (2019). O*NET, widely used in academic research on task content (Acemoglu and Autor, 2011; Autor and Handel, 2013) characterises U.S. occupations through 52 defined abilities, quantifying their importance (on a 1–5 scale) and level (on a 1–7 scale). Examples are provided in Table A1.

PIAAC is a large-scale international survey that assesses adults' proficiency in cognitive skills, job tasks, and skill use at work across countries. It includes a broad set of work-related questions covering literacy, numeracy, problem-solving, interpersonal tasks, and types of computer use.

To extend the analysis beyond the U.S., we construct a cross-country, worker-level dataset spanning 50 countries at varying stages of development (Appendix Table A4). The core of this dataset comes from PIAAC, which collected data across three waves (2011–2012, 2014–2015, 2017–2018) in 37 countries, each with samples of several thousand individuals aged 16–65. We supplement this with data from the World Bank's Skills Toward Employment and Productivity survey – STEP (World Bank, 2017), covering 12 low- and middle-income countries with urban samples of individuals aged 15–64, collected between 2012 and 2014. As STEP surveys exclude rural populations, we omit ISCO 6 (skilled agricultural workers and farmers) in all countries for consistency. We also incorporate the China Urban Labor Survey (CULS), conducted in 2023 by the Chinese Academy of Social Sciences that included a task module consistent with PIAAC and STEP.

To examine changes over time, we use data from the second cycle of PIAAC (2022–2023). 17 countries are included in both PIAAC cycles and report occupational information at the ISCO08 1-digit level: Belgium, Canada, Chile, Czechia, Estonia, Finland, France, Hungary, Italy, Japan, Poland, Singapore, Slovakia, South Korea, Spain, the United Kingdom, and the United States. At the time of writing, the second cycle lacks sufficient occupational detail for constructing AI exposure measures or conducting cross-country regression analysis, with only six countries reporting data at the 2-digit ISCO08 level. Hence, we use the first cycle data to construct our measures.

2.2. Abilities selection

The AI exposure index developed by Felten et al. (2021) is based on occupational abilities from O*NET. To derive worker-level exposures from task data, we use U.S. PIAAC survey responses to approximate the distribution of these abilities across occupations in the U.S. Specifically, we identify 24 O*NET abilities—out of the 52 used by Felten et al. (2021)—that can be proxied using PIAAC questions on job tasks.[1] On average, these 24 abilities account for 67% of the total weight across O*NET occupations, while the remaining 28—primarily physical abilities such as trunk strength and multi-limb coordination—account for 33%. As these physical abilities are less likely to be affected by AI, we focus on the subset more relevant to AI-related task transformation.

We replicate the original AIOE index using only the 24 proxyable abilities and find that the results are nearly identical to those based on the full set. The correlation between our modified AIOE scores and the original values is 0.98 (Appendix Figure B1), confirming the robustness of this approach.

2.3. Approximation of O*NET abilities with US PIAAC data

To approximate O*NET abilities using PIAAC data, we adopt a regression-based strategy. We utilise 18 PIAAC questions: 15 related to routine and non-routine task content (following Lewandowski et al., 2022) and three additional questions capturing ICT use and time management (Tables 1–2).[2] For each ability, we identify the optimal set of PIAAC questions that best reproduces the cross-occupational distribution of that ability at the ISCO 2-digit level in the U.S. To ensure reliability, the algorithm selects between three and eight questions per ability and limits inter-question correlation to below 0.3 to reduce multicollinearity. The selected questions exhibit the highest correlations with the importance of each ability across occupations (see Table 1 for questions phrasing and Table 2 for their matching).

[1] For a list and detailed description of abilities, see Table A1 in the Appendix A.

[2] We maintain the highest possible level of comparability between PIAAC and STEP / CULS. For the correspondence between PIAAC and STEP/ CULS questions, see Table A3 in the Appendix A.

We then estimate the importance of each ability through regression, using the selected PIAAC questions as predictors. For each of the 24 O*NET abilities, we estimate the following specification:

$$Y_{a,o} = \sum_{n}^{N} \beta_n Q_{i,o}^n + \epsilon_{i,o} \tag{1}$$

where $Y_{a,o}$ is the O*NET importance of ability a in occupation o, and $Q_{i,o}^n$ denotes the answers of individual i to question n, who is employed in occupation o. We treat all question responses as categorical variables in a nonparametric framework. For instance, if responses are given on a 1–5 scale, we use indicator variables for values 2 through 5, with 1 as the reference category.

Notably, variation in dependent variable $Y_{a,o}$ is at the occupation level, while variation in the explanatory variables occurs at the worker level, allowing us to capture within-occupation heterogeneity. While an alternative approach would involve aggregating survey responses at the occupational level, our worker-level model enables the construction of individual-level AI exposure measures and allows us to quantify variation within occupations.

Table 1. The list of PIAAC questions selected to proxy for O*NET abilities

Q1	Do you manage or supervise other employees?
Q2	The next few questions are about the amount of flexibility you have in deciding how you do your job: To what extent can you choose or change the sequence of your tasks?
Q3	In your job, what proportion of your time do you usually spend cooperating or collaborating with co-workers?
Q4	How often does your job usually involve making speeches or giving presentations in front of five or more people?
Q5	How often does your job usually involve planning your own activities?
Q6	How often does your job usually involve organising your own time?
Q7	And how often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution? The 30 minutes only refers to the time needed to THINK of a solution, not the time needed to carry it out.
Q8	How often does your job usually involve working physically for a long period?
Q9	In your job, how often do you usually read articles in newspapers, magazines or newsletters?
Q10	In your job, how often do you usually read articles in professional journals or scholarly publications?
Q11	In your job, how often do you usually read manuals or reference materials?
Q12	In your job, how often do you usually read bills, invoices, bank statements or other financial statements?
Q13	In your job, how often do you usually fill in forms?
Q14	In your job, how often do you usually calculate prices, costs or budgets?
Q15	In your job, how often do you usually use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques?
Q16	In your job, how often do you usually use email?
Q17	In your job, how often do you usually use spreadsheet software, for example Excel?
Q18	In your job, how often do you usually use a programming language to program or write computer code?

Source: own elaboration based on PIAAC data.

Table 2. The PIAAC questions with the highest correlation with O*NET abilities (importance) in the US

Ability: \ Question:	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18
auditory attention								X								X	X	
category flexibility					X	X	X	X	X	X						X	X	
deductive reasoning					X	X	X	X	X	X						X	X	
flexibility of closure					X	X	X		X	X	X					X	X	
fluency of ideas				X	X		X	X	X	X						X	X	
inductive reasoning				X	X		X	X	X	X						X	X	
information ordering					X	X	X	X	X	X						X	X	
mathematical reasoning						X	X	X	X	X						X	X	
memorisation				X	X			X	X	X						X	X	
number facility	X						X	X	X	X						X	X	
oral comprehension				X	X			X	X	X						X	X	
oral expression				X	X			X	X	X						X	X	
originality				X	X			X	X	X						X	X	
perceptual speed							X			X	X		X	X		X		
problem sensitivity					X	X	X		X	X						X	X	
selective attention							X			X			X			X		
speech clarity				X	X			X	X	X						X	X	
speech recognition				X				X	X	X			X			X	X	
speed of closure					X	X	X	X	X	X						X	X	
stamina				X	X	X		X	X	X						X	X	
time-sharing	X		X				X		X	X	X		X			X		
visualisation							X	X			X	X		X	X			X
written comprehension				X	X			X	X	X						X	X	
written expression				X	X			X	X	X						X	X	

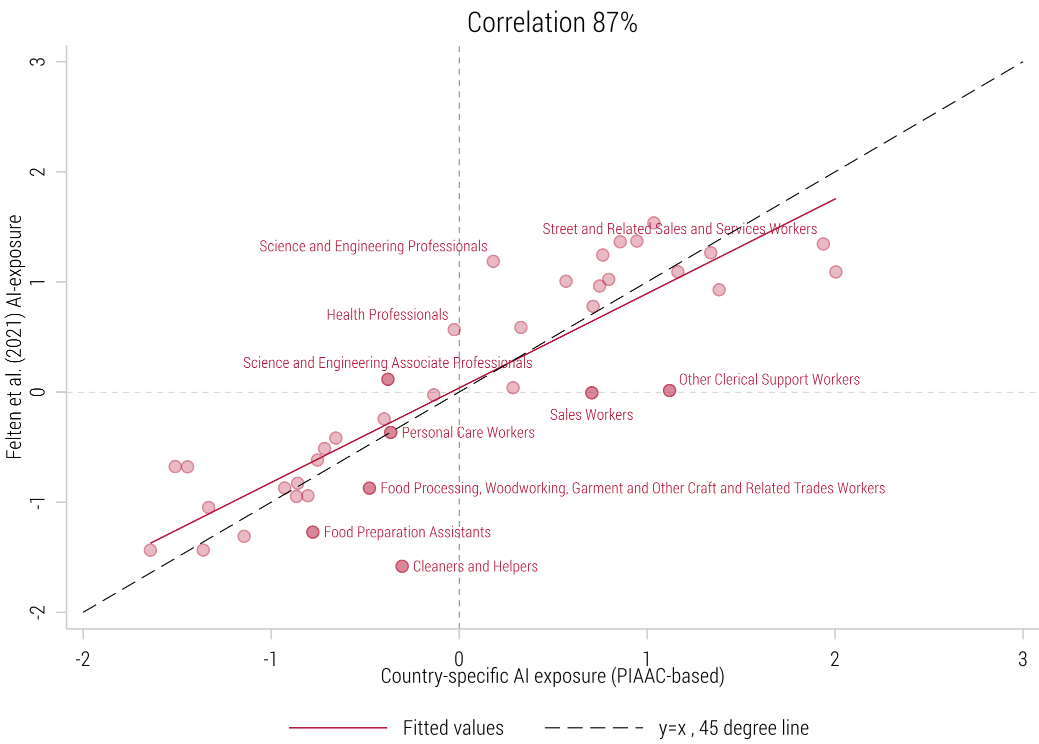
Source: own elaboration on PIAAC and O*NET data.

We first estimate regression coefficients for each PIAAC question response using U.S. data (Tables B1–B4 in Appendix B).[3] These coefficients are then applied to calculate predicted ability levels at the individual level across all countries in the PIAAC dataset. For the U.S, this approach yields a high correlation (94.1%) between the model-predicted importance of abilities and the original O*NET-based importance scores.

Next, we follow a procedure analogous to Felten et al. (2021) to construct AI exposure measures (AIOE), substituting PIAAC-based approximated abilities for the original O*NET weights. This allows us to replicate the distribution of AIOE scores across occupations in the U.S. with considerable accuracy. The correlation between our PIAAC-based AIOE estimates and the original Felten et al. (2021) AIOE index is 87% across 2-digit ISCO occupations in the U.S. (Figure 2).

For a detailed decomposition of within-country AI exposures by specific task items (PIAAC and STEP questions), see the "Variance Decomposition" subsection in Appendix B.

Figure 1. The correlation between AIOE calculated for the US on O*NET and on PIAAC data



Notes: For a detailed list of ISCO08 2-digit occupations, see Table A2 in Appendix A. For the decomposition of the difference between Felten et al. (2021) and PIAAC-based AI exposures, see Figure B2 in Appendix B.
Source: own elaboration based on Felten et al. (2021) and PIAAC data.

[3] For corresponding estimates for STEP/ CULS see Tables B5-B8 in Appendix B. See Table A3 in Appendix A for correspondence between PIAAC and STEP/ CULS questions.

2.4. Econometric methodology

To examine the determinants of cross-country variation in AI exposure, we estimate pooled OLS regressions of the form:

$$AIE_{ijsc} = \beta_0 + \beta_1 T_{sc} + \beta_2 H_{ijsc} + \tau_o + \beta_3 F_{sc} + \beta_4 D_c + \varepsilon_{ijsc} \quad (2)$$

where, AIE_{ijsc} denotes the AI exposure of worker i in occupation j in sector s in country c, T_{sc} captures the ICT intensity in sector s in country c, H_{ijsc} represents individual-level human capital, τ_o are occupation fixed effects, F_{sc} denotes firm characteristics in sector s in country c (including sector fixed effects), and D_c comprises development indicators measured at the country level, also interacted with sector fixed effects.

We operationalise the key variables as follows (Table 3 provides details on data sources):

- ICT intensity: measured as the share of workers using computers at the country-sector level, including a squared term to capture non-linear effects.
- Human capital: includes worker-level variables such as educational attainment, test-based literacy proficiency (four levels), gender, and age (in 10-year groups).
- Occupational structure: controlled for using 2-digit ISCO fixed effects.
- Firm characteristics: include foreign direct investment and both forward and backward participation in global value chains, measured at the country-sector level of International Standard Industrial Classification (ISIC Rev.4), along with 1-digit ISIC sector fixed effects. These are also interacted with development indicators
- Development indicators: the baseline specification uses the (demeaned) log of GDP per capita (PPP) as a proxy for development level. Alternative specifications substitute GDP with learning-adjusted years of schooling, the Human Capital Index, tertiary enrolment rate, ICT Development Index, digital readiness score, or urbanisation rate.[4]

Given the cross-sectional nature of the regressions, the estimates are best interpreted as describing equilibrium allocations of AI-related tasks, rather than causal effects. Nonetheless, ICT intensity and firm characteristics are defined at the aggregate country-sector level and are plausibly exogenous to individual decisions. Human capital, while measured at the individual level, reflects pre-market factors such as education and cognitive skills.

To assess the relative importance of each factor, we use the estimated coefficients to compute a linear prediction of average AI exposure by country, $\overline{AIE_c}$, and apply the covariance-based decomposition proposed by Morduch and Sicular (2002). The contribution of a variable group, k, to the variance of AIE_c is given by:

$$\sigma_k = \frac{cov(\beta_k \bar{X}_c^k, \overline{AIE_c})}{var(\overline{AIE_c})} \quad (3)$$

Finally, to estimate AI exposure in countries lacking worker-level task data, we predict occupational AI exposure using OLS regressions of the form:

$$AIE_{kjc} = \beta_{j0} + \beta_{j1} GDP_c + \beta_{j2} T_c + \beta_{j3} H_c + \beta_{j4} G_c + \beta_{j5} I_c + \gamma_{kj} + \varepsilon_{kjc} \quad (4)$$

[4] In cross-sectional setting, we cannot control for multiple development indicators at once.

where AIE_{kjc} is the AI exposure of occupation k, a 2-digit ISCO subcategory within 1-digit occupation j, in country c, GDP_c is GDP per capita (PPP, log-transformed), T_c, H_c, G_c, and I_c represent proxies for technology use, human capital, globalisation, and infrastructure, respectively; and γ_{kj} are fixed effects for 2-digit ISCO occupations within each 1-digit group.

This approach builds on Lewandowski et al. (2023), who estimated country-specific routine task intensity based on development levels and proxies for technology adoption, skill supply, participation in global value chains, and structural change. In contrast, we draw on a broader set of variables to better capture technological capacity and human capital across countries (see Table 3).

Table 3. Control variables and data sources

Variable	Source
Technology	
ICT intensity – share of workers using computers by sector-country	PIAAC/ STEP
Share of the population with internet access	World Bank World Development Indicators (WDI)
ICT development index (IDI)	ITU- The UN agency for digital technologies
Digital Readiness Index (DRI) and its components: technology adoption and infrastructure	CISCO
Human Capital (skill supply and health)	
Human Capital Index (HCI) and its components: learning adjusted years of school (LAYS) and survival rate from age 15-60 (AMRT)	WDI
School Enrolment rate, primary	WDI
School Enrolment rate, tertiary	WDI
Share of population between 15 and 64	WDI
Globalisation	
Share of ICT in Imported Goods	WDI
Foreign Direct Investment as % of GDP (FDI)	WDI
GVC participation (total, backward or forward) and exports	EORA (Lenzen et al., 2013, 2012)
Infrastructure	
Share of population with access to electricity	WDI
Urbanisation rate	WDI
Development	
Natural Logarithm of the GDP pc	WDI

Notes: Technology adoption (DRI score component) includes: internet usage, mobile cellular subscriptions, and cloud services. Technology infrastructure (DRI score component) includes: fixed broadband subscriptions, households' internet access, secure internet services, and mobile broadband subscriptions.

Source: own elaboration.

We estimate prediction models separately within 1-digit ISCO occupational groups, using a stepwise variable selection procedure to identify the optimal specification. First, we implement both forward and backward selection methods across a range of p-value thresholds (0.01 to 0.5). Backward selection iteratively removes variables with p-values above the threshold, while forward selection adds variables whose p-values fall below it. Each model includes log GDP per capita as a baseline control.

Second, we evaluate model performance using leave-one-out cross-validation (LOOCV). This procedure estimates each model using all but one country, fits the model, and then predicts the excluded observation. The process is repeated for each country in the sample. For each 1-digit ISCO occupation, we retain the best-performing model from both selection strategies based on predictive accuracy. We limit each model to a maximum of six explanatory variables to mitigate overfitting. To determine which variables to exclude, we apply a variance-covariance decomposition and drop those contributing least to the explained variance.

Third, we review the selected models to eliminate redundancy. When a model includes both a composite index (e.g., the Human Capital Index) and its component (e.g., learning-adjusted years of schooling), we retain only the underlying component. We prioritise original data sources over synthetic indicators, aiming for greater data-driven variability and interpretability.

Fourth, we re-run LOOCV to select the better-performing model from each forward–backward pair. We then augment these models with fixed effects for 2-digit ISCO08 occupations to allow predictions at a more granular occupational level. Table 4 lists the variables used in the final prediction models, and Table B9 reports the corresponding regression coefficients.

The final estimation sample includes 49 countries,[5] and we generate predictions for 53 countries—mostly low- and middle-income economies (Appendix Table A5).[6] The most frequently selected predictors of AI exposure include GDP per capita, the ICT Development Index, internet access rates, participation in global value chains, access to electricity, and the Digital Readiness Index.

Table 4. The variables used in prediction models, by 1-digit ISCO occupations

Variable	ISCO 1	ISCO 2	ISCO 3	ISCO 4	ISCO 5	ISCO 7	ISCO 8	ISCO 9
GDP pc	X	X	X	X	X	X	X	X
(GDP pc)^2			X					
Human Capital Index		X						
Learning adjusted years of schooling	X		X					
University enrolment				X				
Survival rate from age 15-60					X			
Population with electricity					X	X	X	
Urbanisation	X	X						
ICT development index		X	X	X	X	X	X	X
Digital Readiness Index				X		X		X
Internet use	X			X	X	X	X	X
Technology Infrastructure					X		X	
Technology adoption			X					
Global Value Chains participation				X			X	X
ICT imports						X		X

Notes: School enrolment rate, foreign direct investments, and exports where also tested, average hours worked per employee, but not selected to any model.
Source: Own elaboration based on PIAAC, STEP, WB, EORA, ITU, and CISCO data.

[5] Serbia is omitted due data unavailability.

[6] Due to missing data, exposures in Bahrain (ISCO 3, 5, 7, 8 are missing), Brunei (ISCO 3, 5, 7, 8 are missing), Hong Kong (ISCO 3, 5, 7, 8, 9 are missing) are incomplete.

3. Results

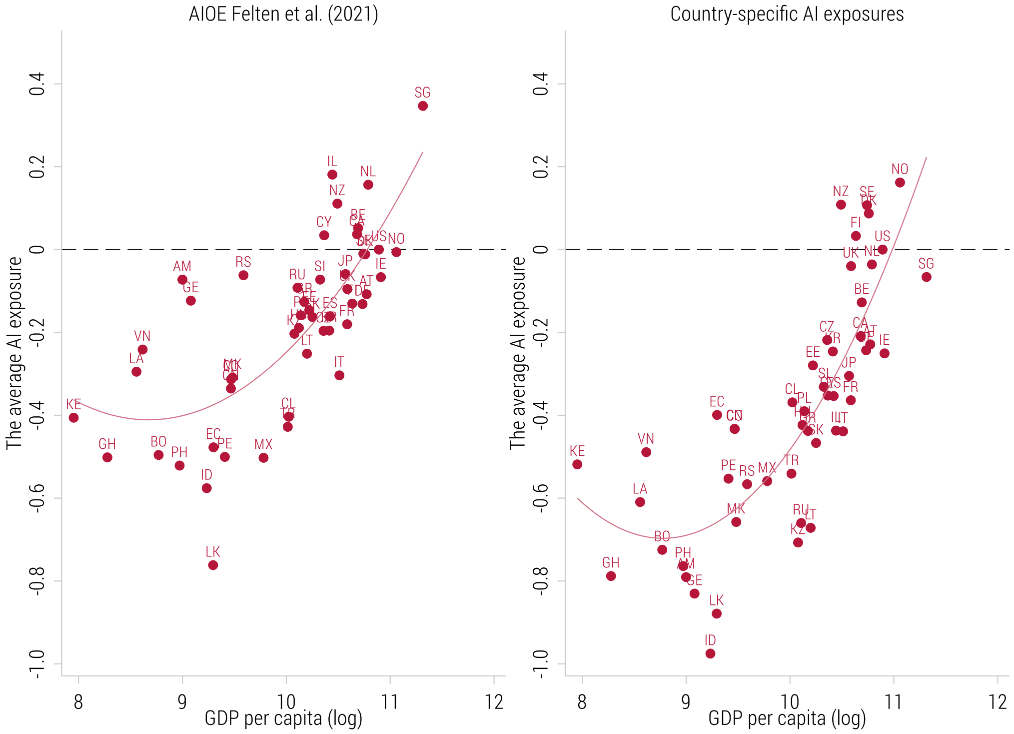
3.1. Descriptive evidence on cross-country differences in AI exposures

Adjusting AI exposure estimates for cross-country differences in task composition reveals profound differences across the development spectrum (Figure 2). Comparing survey-based, worker-level AI exposures (right panel of Figure 2) with the globally applied AIOE index from Felten et al. (2021) (left panel), we find that incorporating country-specific task data substantially amplifies cross-country variation beyond what is captured by occupational structure alone. While higher average AI exposure is consistently associated with greater levels of development, the gradient is considerably steeper when using the task-adjusted, country-specific measure.

Under the original AIOE, the average AI exposure in the least developed countries is approximately 0.5 U.S. standard deviations below that of the United States—reflecting only differences in occupational composition. In contrast, the task-adjusted measure shows a gap of about one U.S. standard deviation, indicating that within-occupation task differences account for a substantial share of the exposure gap.

To validate this, we apply U.S.-based PIAAC-derived exposures to all countries and find results closely aligned with those from the original AIOE (Figure B3, Appendix). This confirms that the observed differences between survey-based and AIOE-based exposures are driven by the use of country-specific task data—not by the substitution of PIAAC questions for O*NET abilities in the construction of AI exposure indices.

Figure 2. The comparison of the average Felten et al. (2021) and PIAAC/STEP-based AI exposures at the country level



Note: the Spearman correlations between the AI exposure calculated with the most detailed information available in PIAAC/STEP and exposure calculated only with the set of questions and answers as available in STEP are 74% (country-level average) and 81% (country-occupation-level). AI exposures standardised with the US mean and standard deviation. Source: Own calculations based on the O*NET, PIAAC, STEP and CULS data.

To quantify the respective contributions of occupational structure and task content to cross-country variation in AI exposure, we decompose the score for each country into three components

- Occupational structure: calculated using Felten et al. (2021) AIOE at the 2-digit ISCO level; variation reflects only differences in countries' occupational distributions at the 2-digit ISCO level[7] (left panel of Figure 2).
- Task-related exposure: the difference between survey-based country-level exposure and exposure derived from applying U.S. PIAAC-based occupational scores to each country (difference between right panels of Figures 2 and B3).
- Measurement change: the residual difference between U.S. PIAAC-based exposures and original AIOE exposures applied globally, capturing methodological differences in mapping AI to jobs between Felten et al. (2021), who used O*NET abilities, and our study using PIAAC job tasks (difference between right and left panels of Figure B3).

Task-related components contribute a noticeable share of countries' AI exposure (Figure 3). Using a variance-covariance decomposition (Morduch and Sicular, 2002), we find that they account for 47% of the cross-country variance in average AI exposure—nearly as much as differences in occupational structure (52%). The task component is particularly significant in low-income countries (Figure 3). The measurement change contributes just 1% to the total variance, suggesting that methodological differences between PIAAC-based and O*NET-based mappings have minimal impact compared to actual variation in tasks and occupations.

Figure 3. Decomposition of the differences in AI exposure by country

Note: Countries sorted by average country-level exposure.
Source: Own calculations based on the O*NET, PIAAC, STEP and CULS data.

[7] For Austria, Canada, Estonia, Finland, and Philippines we use 1-digit ISCO due to data availability.

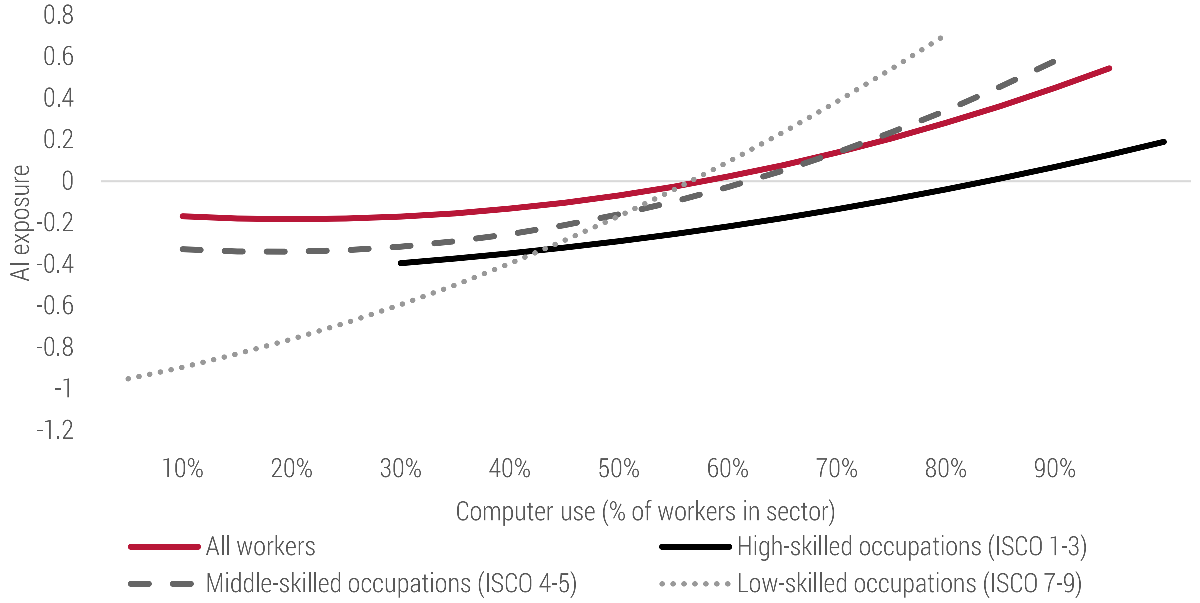
3.2. Determinants of worker-level AI exposure and cross-country differences

Estimating worker-level models of task-based AI exposure (Equation 2), we identify ICT intensity and socio-economic characteristics as key correlates. Table 5 reports OLS estimates for the full sample (column 1) and for a subset of countries with occupational data at the 2-digit ISCO level (columns 2–3). Column 2 includes ISCO-1D fixed effects, consistent with column 1, while column 3 incorporates ISCO-2D fixed effects, capturing variation in AI exposure within more granular occupational categories.

Greater access to digital technologies is positively associated with AI exposure, particularly in country-sectors where over 50% of workers use computers (Table 5). Introducing a squared term to account for nonlinearity, we observe that AI exposure is largely unresponsive to computer use below the 50% threshold, but increases markedly above it (Figure 4). For example, a 17 pp increase in computer use—comparable to the gap between the U.S. (75%) and China (58%)—corresponds to a 0.13 standard deviation rise in AI exposure, equivalent to 30% of the U.S.–China differential in average exposure.

This effect is especially pronounced among workers in low- (ISCO 7-9) and middle-skilled (ISCO 4-5) occupations, where both AI exposure and computer use are generally lower than in high-skilled occupations (ISCO 1-3, Figure 4).[8] Nonetheless, the relationship between computer use and AI exposure is strongest in these routine-intensive, lower-skilled occupations.

Figure 4. Estimated relationship between computer use and AI exposure, for all workers and by occupational group



Note: Based on the estimates presented in Column 3 of Table 5. For each category of workers, we select a range of computer use which includes 90% of workers in each category (we omit bottom and top 5%). Median computer use among ISCO 1-3 is 73.5%, among ISCO 4-5 is 56.0%, and among ISCO 7-9 is 40.1%.
Source: Own estimations based on PIAAC, STEP, WB, and EORA data.

[8] Regression results by occupational groups are available upon request.

Table 5. The correlates of individual AI exposures based on OLS cross-country regression with occupational controls

Variable	(1)	(2)	(3)
ICT intensity (sector share of workers using computers)	-0.388	-0.503**	-0.531**
	(0.091)	(0.096)	(0.230)
ICT intensity ^ 2	1.232***	1.354***	1.304***
	(0.194)	(0.195)	(0.182)
Education: Secondary	0.165***	0.159***	0.174***
	(0.012)	(0.013)	(0.012)
Education: Tertiary	0.344***	0.346***	0.360***
	(0.018)	(0.019)	(0.017)
Low literacy proficiency (levels 1 or lower)	-0.097***	-0.093***	-0.094***
	(0.012)	(0.012)	(0.011)
Medium literacy proficiency (level 3)	0.089***	0.084***	0.075***
	(0.009)	(0.010)	(0.009)
High literacy proficiency (levels 4 and 5)	0.118***	0.116***	0.101***
	(0.014)	(0.016)	(0.014)
Gender: Woman	-0.067***	-0.053***	-0.181***
	(0.012)	(0.012)	(0.011)
Age: 16-24	-0.170***	-0.162***	-0.163***
	(0.014)	(0.014)	(0.014)
Age: 35-44	-0.000	0.001	-0.006
	(0.008)	(0.008)	(0.008)
Age: 45-54	-0.057***	-0.055***	-0.064***
	(0.010)	(0.010)	(0.010)
Age: 55-65	-0.174***	-0.171***	-0.181***
	(0.012)	(0.013)	(0.012)
Backward GVC participation (GVCB) share in exports (std.)	-0.044	-0.434***	0.018
	(0.073)	(0.109)	(0.073)
GVCB share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	-0.003	-0.024	0.045
	(0.085)	(0.088)	(0.080)
Forward GVC participation (GVCF) share in exports (std.)	-0.427***	-0.065	-0.287***
	(0.104)	(0.077)	(0.107)
GVCF share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.588***	0.576***	0.620***
	(0.144)	(0.146)	(0.145)
FDI / GDP	-0.023***	-0.022***	-0.020***
	(0.007)	(0.007)	(0.006)
FDI / GDP * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.022	0.021	0.008
	(0.015)	(0.016)	(0.015)
Ln(GDP per capita) –mean(Ln(GDP per capita))	-0.045	-0.035	-0.027
Occupation fixed effects	ISCO 1D	ISCO 1D	ISCO 2D
Observations	161,509	130,812	130,812

Note: All regressions contain sector fixed effects (at 1-digit ISIC Rev.4 classification) and sector fixed effects interacted with GDP per capita. Base categories – Men, Primary education, aged 25-34, Lower-medium literacy proficiency (level 2).China is omitted due to data restrictions, Laos, Macedonia, Philippines, and Sri Lanka are omitted due to unavailability of some control variables. Austria, Canada, Estonia, and Finland are omitted in columns (2) and (3) due to the lack of ISCO 2-digit occupations. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Own estimates based on PIAAC, STEP, WB, and EORA data.

Human capital emerges as the strong predictor of AI exposure: higher levels of education and literacy proficiency are associated with significantly greater exposure (Table 5). For instance, a worker with the highest literacy proficiency (levels 4–5) is expected to have an AI exposure score 0.12 points higher than an otherwise similar worker with lower proficiency (level 2). This pattern aligns with previous (Cazzaniga et al., 2024; Comunale and Manera, 2024; Pizzinelli et al., 2023), which find that better-educated individuals are more exposed to AI. However, while those studies focus on differences across occupations, our worker-level approach demonstrates that this relationship persists within occupations, even within the 2-digit ISCO occupations (column 3 of Table 5). More skilled workers tend to perform more AI-exposed tasks, particularly those involving analytics and computer use, resulting in systematically higher exposure than their less skilled counterparts in the same occupations. Additionally, we find that women, as well as the youngest and oldest workers, are less exposed to AI than men and prime-aged workers in comparable occupations (Table 5).

Firm-level characteristics linked to globalisation also contribute to AI exposure. In a country with average GDP per capita in our sample (e.g., Slovakia or Estonia), higher forward participation in global value chains (GVCs)—measured as the domestic value added embedded in partner countries' exports (Borin and Mancini, 2019, 2015)—is associated with lower AI exposure (Table 5, column 3). This is particularly relevant for many Sub-Saharan African and Latin American economies that specialise in upstream GVC tasks, such as commodity exports in agriculture and mining, with limited use of imported inputs (Hanson, 2017; Taglioni and Winkler, 2016). The interaction between forward GVC participation and GDP per capita is positive, indicating that the negative relationship weakens with higher income. Specifically, the effect disappears at 146% of the sample's average GDP per capita—approximately the level of Finland—while it is more pronounced in low- and middle-income countries (LMICs). These findings are consistent with evidence that GVC-intensive work in LMICs is more routine-based (Lewandowski et al., 2024) and, as we show, less connected to advanced, AI-relevant tasks. We also find that a higher share of foreign direct investment (FDI) in GDP is negatively associated with AI exposure. While FDI is not significantly correlated with routine task intensity (Lewandowski et al., 2022), it appears linked to jobs with fewer AI-relevant, ICT-intensive tasks.

Next, we use the estimated coefficients to assess the contributions of each group of explanatory variables to the countries' average AI exposure. We apply the covariance-based decomposition (Equation 3) to quantify their role in explaining cross-country differences. As the regressions control for 2-digit ISCO fixed effects, this decomposition sheds light on factors behind the within-occupation variation in AI exposure (Figure 4). Starting from the model using GDP per capita (Table 5, column 3), we re-estimate the specification substituting GDP with alternative development indicators to evaluate which dimensions are most strongly associated with variation in exposure.

Our models explain 75–78% of the cross-country variance in workers' AI exposure (Table 6). Across all specifications, ICT intensity is the dominant factor, accounting for 50-64% of the explained variance. Occupational structure contributes approximately 15%. Human capital—measured through education, literacy proficiency, gender, and age—explains about 11%, with the largest share (8%) attributable to literacy proficiency (detailed results available upon request). Observable firm characteristics contribute between 3% and 20%, generally less than human capital.

Interestingly, GDP per capita contributes negatively to the cross-country variance in AI exposure (approximately -5%, Table 6), suggesting that conditional on ICT intensity, human capital, and other explanatory variables, within-occupation, task-related differences are even more pronounced than according to differences in development levels. When GDP is replaced with alternative development indicators, the negative contributions become even larger. This is particularly evident for technological capacity measures, such as the ICT Development Index (-33.2%) and the Digital Readiness Index (-14.4%), and human capital indicators capturing education quality—e.g., the Human Capital Index (-17.2%) and learning-adjusted years of schooling (-18.1%). These results suggest that the development gradient in AI exposure, when measured through task differences within occupations, is stronger than would be expected based solely on income, technological infrastructure, or formal education metrics.

Other development proxies, such as urbanisation, explain a smaller share of the cross-country variance (e.g., 4.7%).[9] Overall, our findings highlight the central role of ICT infrastructure and digital technology use in shaping workers' AI exposure across countries at different development levels.

Table 6. The decomposition of the cross-country variance in country-specific AI exposure (in % of variance)

Development measure used:	GDP per capita (log)	ICT development index	Digital Readiness Index	Human Capital Index	Learning adjusted years of schooling	Tertiary education enrolment rate	Urbanisation rate
ICT intensity	50.0	63.7	56.5	57.2	58.2	52.9	49.4
Human capital	10.5	11.4	11.3	9.8	9.9	11.5	11.3
Firm characteristics	7.5	19.5	8.9	10.3	9.9	-6.9	-3.3
Occupational structure	15.4	15.2	15.6	15.1	15.0	15.7	15.5
Development indicators	-5.4	-33.2	-14.4	-17.2	-18.1	3.8	4.7
Explained variance	78.0	76.6	77.9	75.0	75.3	77.0	77.7

Note: using variance-covariance decomposition (Morduch and Sicular, 2002).
Source: Own estimates based on PIAAC, STEP, WB, EORA, ITU and CISCO data.

[9] We have also used development proxies used in out of sample predictions (see Table 4), such as the share of population with electricity, ICT imports, general export, school enrolment, technology adoption, technology infrastructure. For brevity, we do not present these results, they are available upon request.

3.3. AI exposures of occupational groups across the development spectrum

We now turn to occupation-level results, combining survey-based AI exposure estimates for 49 countries with regression-based predictions for 53 additional countries lacking task-level survey data. Appendix Table A5 lists all countries and their classification into income groups: lower- and upper-tier high-income countries (HICs), upper-middle-income countries (UMICs), and low- and lower-middle-income countries (LMICs).[10] While exposures are predicted at the 2-digit ISCO-08 level, we present results at the 1-digit level for clarity.

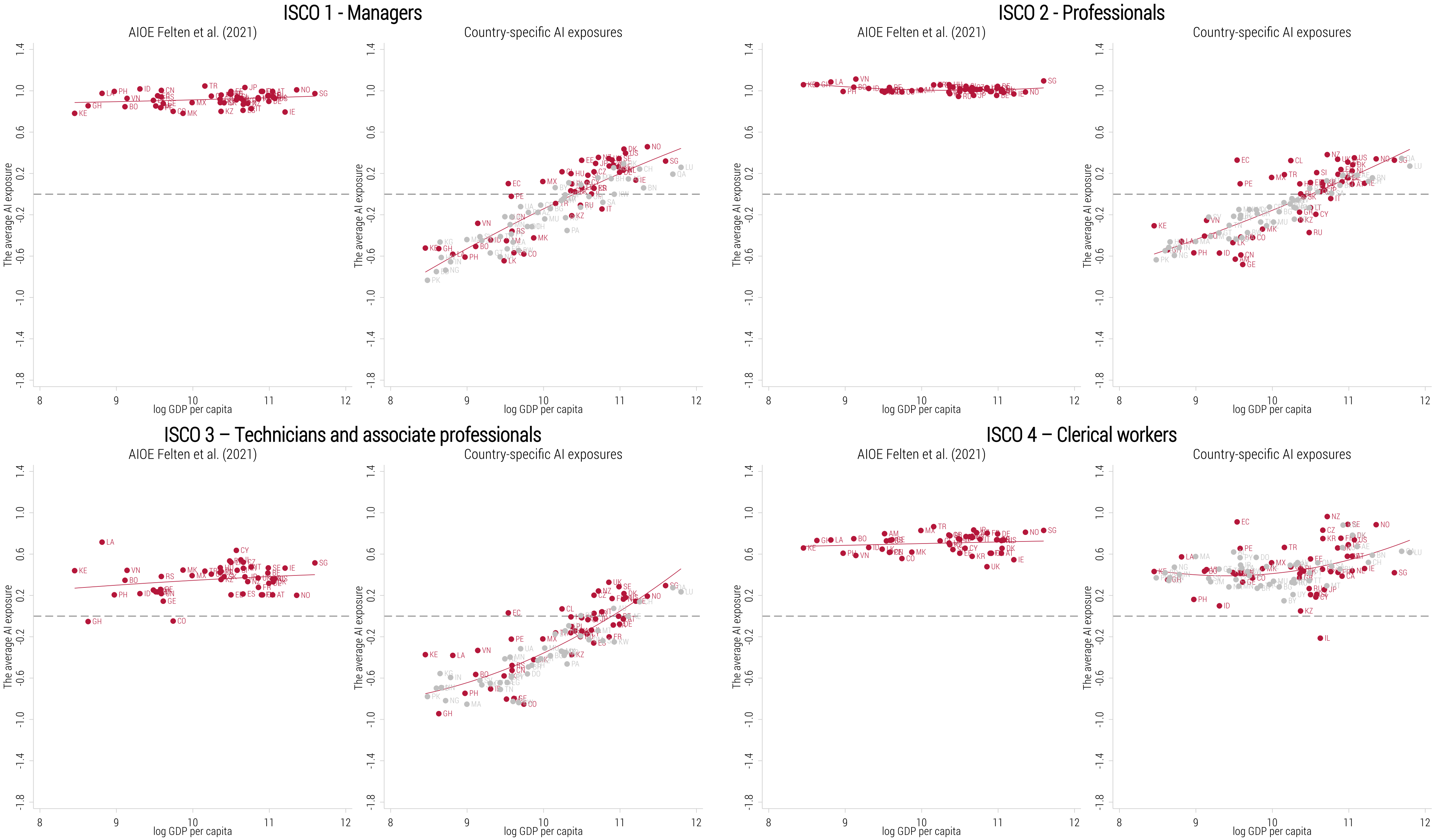
The predicted AI exposures replicate the development patterns observed in the survey data, consistent with the findings of Lewandowski et al. (2023), who used a similar methodology to predict routine task intensity in countries without the required survey data.

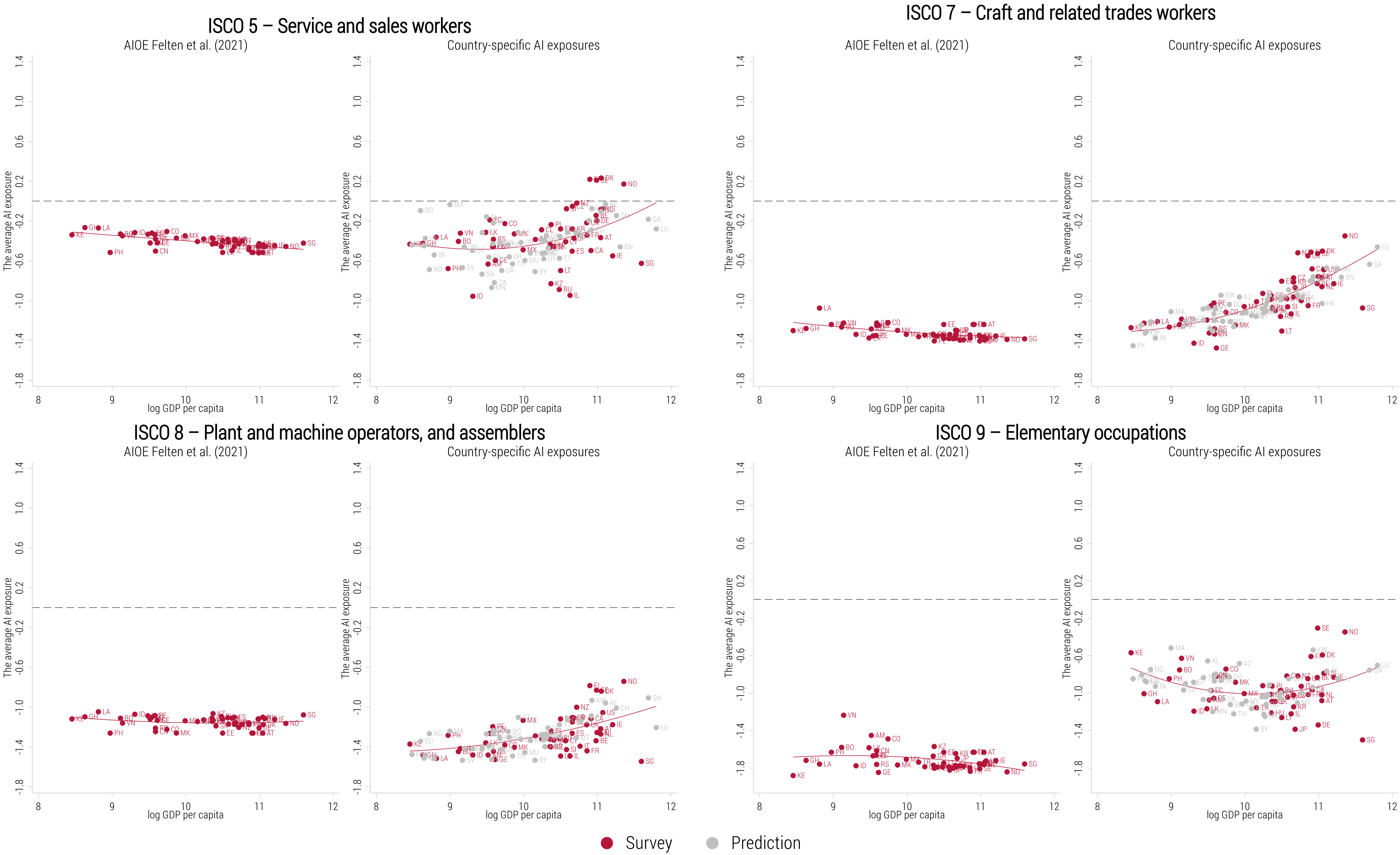
For each 1-digit ISCO-08 occupational group, our task-adjusted exposure measure shows considerably more cross-country variation than the AIOE index from Felten et al. (2021) (Figure 5). The variation in AIOE (left panels) arises solely from differences in the composition of 2-digit occupations within each 1-digit group. In contrast, our measure (right panels) incorporates cross-country differences in task content within occupations, offering a more nuanced picture.

The greatest cross-country variation appears among high-skilled occupations (ISCO 1–3), including managers, professionals, and technicians. In these occupations, AI exposure rises clearly with GDP per capita, reflecting increased use of ICT-intensive tasks and greater ICT capital intensity in more developed countries. For middle-skilled occupations (ISCO 4–5), the relationship between GDP per capita and AI exposure is less pronounced. Exposure is relatively flat across much of the development spectrum, but increases sharply in the most advanced HICs, particularly Scandinavian countries. Notably, clerical support workers (ISCO 4) consistently exhibit the highest levels of AI exposure across all country groups, suggesting that this occupational group is likely to be globally affected by AI adoption. Among low-skilled occupations (ISCO 7–9), AI exposure also increases with development, although the gradient is less steep than for high-skilled workers. A notable exception is elementary occupations (ISCO 9), where no consistent relationship with GDP per capita emerges. Across low-skilled groups, average exposures are negative—i.e., lower than the U.S. mean—and consistently below those observed for high- and middle-skilled occupations.

[10] Table 4 in subsection 2.4 provides the list of variables used in the prediction models and Table B9 in Appendix B shows the regression coefficients. We do not extrapolate beyond the range used to build the prediction models, specifically we do not predict AI exposures for countries with a GDP per capita below Kenya ($2687 PPP, on average, between 2011 and 2016), the poorest country in the survey sample.

Figure 5. The comparison of the average Felten et al. (2021) and the PIAAC-based US AI exposures at the country level by ISCO-1d occupational groups and out-of-.sample prediction of AI exposures





Note: The values of the AI exposures are standardised with the US mean and standard deviation.
Source: Own calculations based on PIAAC, STEP, WB, EORA, ITU, and CISCO data.

We next combine AI exposure estimates—both survey-based and predicted—with the most recent occupational structure data from the International Labour Organization (ILO). Our final dataset covers 84 countries (Appendix Table A5), representing approximately 86% of global employment.[11]

Using AI exposures weighted by employment across all countries and occupations, we define least exposed jobs as those in the bottom quartile (25th percentile) of the global AI exposure distribution and most exposed jobs as those in the top quartile (75th percentile).

High-income countries account for 60.1% of the world's most AI-exposed workers, but only 16.5% of the least exposed (Table 7). Upper-middle-income countries—including Brazil, China, and Turkey—host roughly equal shares of the most (25.6%) and least (33.4%) exposed workers. In contrast, low- and lower-middle-income countries, such as India, account for only 14.3% of the most exposed but half (50%) of the least exposed workers globally.

Table 7. Global distribution of the most/least AI-exposed workers. by country groups (in % of employment in a given category)

	Low or lower-middle income	Upper-middle income	Lower-tier high-income	Upper-tier high-income
Most exposed (top 25%)	14.3	25.6	15.9	44.2
Least exposed (bottom 25%)	50.0	33.4	8.4	8.1
Total employment	39.9	33.9	8.5	17.7

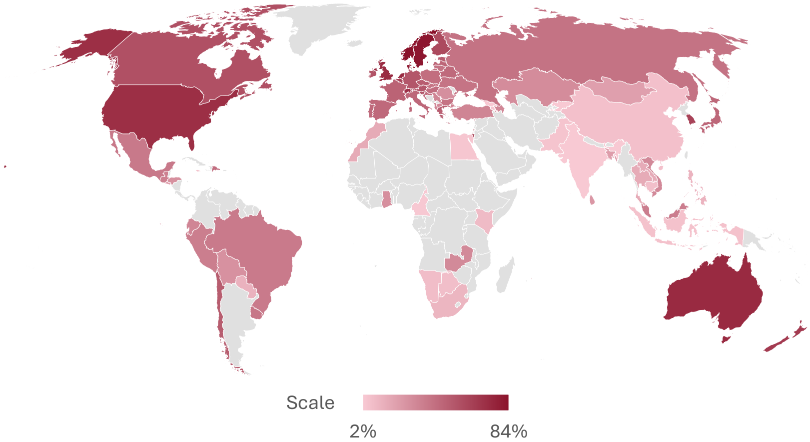
Note: Country group classifications follow Appendix Table A5.
Source: Own calculations based on PIAAC, STEP, WB, EORA, ITU, CISCO, and ILO data.

As a result, countries with the highest shares of highly AI-exposed workers are predominantly high-income economies. In contrast, major emerging markets such as China and India have comparatively low shares of highly exposed workers (Figure 6). Meanwhile, upper-middle-income countries (e.g., Brazil, Mexico) and lower-middle-income countries (e.g., Indonesia, the Philippines) record the highest employment shares of workers in the least exposed category globally.

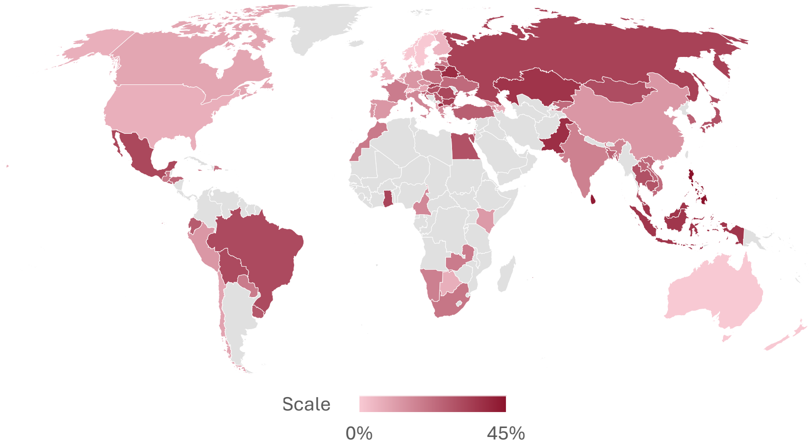
[11] We exclude tax heavens, petrostates, island countries, and countries without credible employment data.

Figure 6. The share of workers who are the most and the least exposed to AI globally, as a share of countries' employment

Top 25% of the most exposed workers



Bottom 25% of the least exposed workers



Note: The most exposed workers defined as the top quartile of the global distribution of AI exposure. The least exposed – as the first quartile

Source: Own calculations based on PIAAC, STEP, WB, EORA, ITU, CISCO, and ILO data.

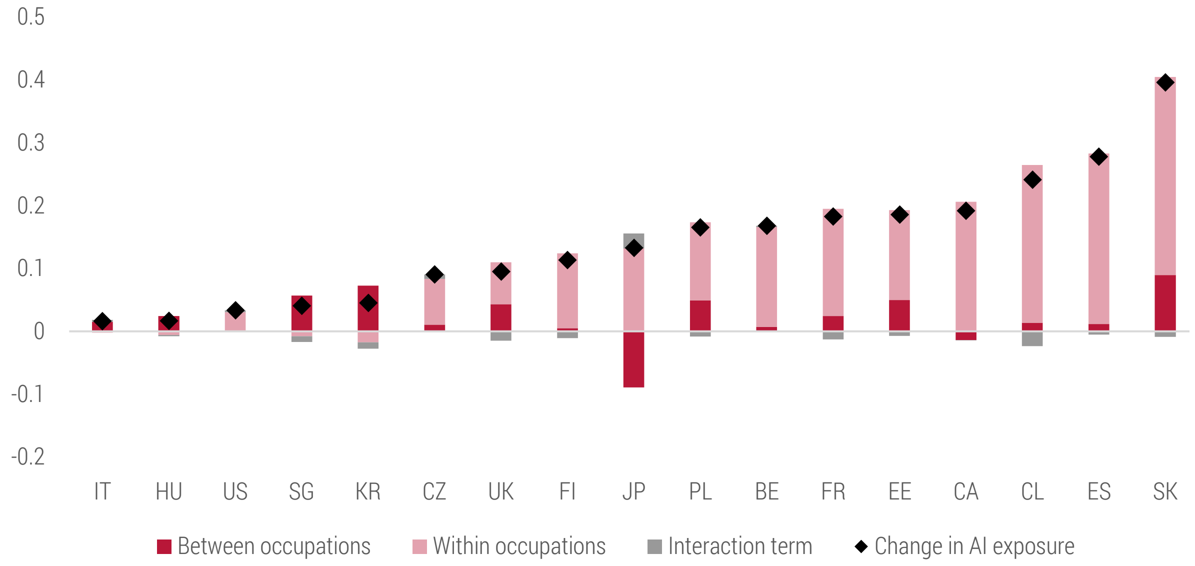
3.4. Change in AI exposure between the early 2010s and the early 2020s

Finally, we examine changes in workers' AI exposure over roughly a decade, comparing results based on the first (between 2011 and 2018) and the second (2022-2023) cycles of the PIAAC survey. At the time of writing, data with 1-digit ISCO08 occupations are available for 17 countries across both waves.

In all countries with available data, average AI exposure increased, with the largest gains observed in lower-tier high-income countries such as Slovakia, Chile, and Estonia. Notably, the initial level of AI exposure is strongly and negatively correlated with subsequent changes (correlation coefficient: -0.50), indicating convergence in exposure levels, at least among high-income economies.

To unpack the mechanisms behind these changes, we conduct a shift-share decomposition at the 1-digit ISCO level (Figure 7). In nearly all countries, the rise in AI exposure is primarily explained by within-occupation changes—i.e., shifts in task content within existing occupations. This component also accounts for nearly all of the cross-country variation in AI exposure change over time (Table 8). In contrast, the between-occupation component—reflecting changes in the occupational composition of employment—contributes relatively little and is negatively associated with the cross-country variance. This suggests that countries experiencing greater increases in AI exposure did so largely through evolving job tasks within occupations rather than structural shifts in employment. These findings underscore the importance of using survey-based, task-level data that account for cross-country differences in the nature of work.

Figure 7. The shift-share decomposition of the change in the average workers' AI exposure between the early 2010s and the early 2020s, by country



Source: Own calculations based on PIAAC and O*NET data.

Table 8. The share of cross-country variance attributed to particular components of the shift-share decomposition of AI exposure change wbetween the early 2010s and the early 2020s

	Between occupations	Within occupations	Interaction term
Share of explained variance	6.0%	96.9%	-2.6%

Note: using variance-covariance decomposition (Morduch and Sicular, 2002).
Source: Own calculations based on PIAAC data.

4. Conclusions

This paper presents a task-adjusted, country-specific measure of workers' AI exposure across a wide range of development contexts. Adapting the widely used AIOE index by Felten et al., (2021) to U.S. PIAAC data, we constructed a worker-level AI exposure metric. We then extended this measure to 50 countries using comparable survey data and developed regression-based predictions for 53 more countries without survey coverage. In total, our analysis covers 103 countries, representing approximately 86% of global employment.

A central finding is that accounting for worker-level tasks is essential to understanding AI exposure. Doing so reveals significant cross-country heterogeneity, particularly along the development spectrum. On average, workers in low-income countries experience AI exposure levels roughly one U.S. standard deviation below those in high-income countries. Approximately 47% of this cross-country variation is attributable to differences in occupational task content. This variation is especially pronounced among high-skilled occupations, where workers typically engage in more abstract, non-routine tasks—activities that vary widely across countries depending on technological capacity, skill supply, and positions in global value chains (Caunedo et al., 2023; Lewandowski et al., 2022). By contrast, AI exposure among medium- and low-skilled occupations shows little development gradient, as relevant job tasks are more uniform across contexts.

Using regression-based decompositions, we attribute most of cross-country variation in AI exposure to differences in the intensity of ICT in the economy and its technological capabilities. We also find that AI exposure is positively associated with workers' education and skill levels: more educated and higher-skilled individuals consistently report greater exposure to AI-related tasks. When quantifying global variation, high-income countries host the largest share of workers in highly AI-exposed occupations, while low-income countries concentrate a much greater share of workers in less exposed roles. Emerging economies such as China and India show relatively low average AI exposure, whereas countries like Brazil, Mexico, Indonesia, and the Philippines have a large proportion of workers in occupations with minimal AI exposure.

For the subset of high-income countries with two waves of PIAAC data, we observe a clear increase in AI exposure between the early 2010s and early 2020s. This trend is almost entirely driven by within-occupation changes in task composition, further highlighting the importance of capturing evolving task structures in exposure assessments.

Understanding variation in AI exposure across occupations and countries has important policy implications. Advanced economies—where AI-exposed workers are most concentrated—are likely to face both the opportunities and disruptions of AI adoption earlier and more intensively (Cazzaniga et al., 2024). However, widespread displacement is unlikely to occur rapidly, as the automation of highly exposed tasks remains constrained by cost and feasibility (Svanberg et al., 2024). Meanwhile, emerging economies may face challenges in adopting AI due to limited digital infrastructure and technological readiness, potentially exacerbating existing economic and technological disparities (Gmyrek et al., 2024).

A limitation of our exposure-focused approach is that we do not determine whether AI will complement or substitute human labour. While this distinction is of key importance, we believe it should be assessed based on empirical evidence on the actual AI adoption rather than arbitrary assumptions about the extent of substitutability of particular tasks or their bundles, as would be required in our approach.

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Appendix A – Technical details

Table A1. The list of O*NET abilities

Abilities approximated with PIAAC/ STEP:	
auditory attention	The ability to focus on a single source of sound in the presence of other distracting sounds.
category flexibility	The ability to generate or use different sets of rules for combining or grouping things in different ways.
deductive reasoning	The ability to apply general rules to specific problems to produce answers that make sense.
flexibility of closure	The ability to identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material.
fluency of ideas	The ability to come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).
inductive reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
information ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).
mathematical reasoning	The ability to choose the right mathematical methods or formulas to solve a problem.
memorisation	The ability to remember information such as words, numbers, pictures, and procedures.
number facility	The ability to add, subtract, multiply, or divide quickly and correctly.
oral comprehension	The ability to listen to and understand information and ideas presented through spoken words and sentences.
oral expression	The ability to communicate information and ideas in speaking so others will understand.
originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
perceptual speed	The ability to quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns. The things to be compared may be presented at the same time or one after the other. This ability also includes comparing a presented object with a remembered object.
problem sensitivity	The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognising that there is a problem.
selective attention	The ability to concentrate on a task over a period of time without being distracted.
speech clarity	The ability to speak clearly so others can understand you.
speech recognition	The ability to identify and understand the speech of another person.
speed of closure	The ability to quickly make sense of, combine, and organise information into meaningful patterns.
stamina	The ability to exert yourself physically over long periods of time without getting winded or out of breath.
time sharing	The ability to shift back and forth between two or more activities or sources of information (such as speech, sounds, touch, or other sources).
visualisation	The ability to imagine how something will look after it is moved around or when its parts are moved or rearranged.
written comprehension	The ability to read and understand information and ideas presented in writing.
written expression	The ability to communicate information and ideas in writing so others will understand.

Abilities that cannot be approximated with PIAAC/ STEP data	
arm-hand steadiness	The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.
control precision	The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.
depth perception	The ability to judge which of several objects is closer or farther away from you, or to judge the distance between you and an object.
dynamic flexibility	The ability to quickly and repeatedly bend, stretch, twist, or reach out with your body, arms, and/or legs.
dynamic strength	The ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue.
explosive strength	The ability to use short bursts of muscle force to propel oneself (as in jumping or sprinting), or to throw an object.
extent flexibility	The ability to bend, stretch, twist, or reach with your body, arms, and/or legs.
far vision	The ability to see details at a distance.
finger dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
glare sensitivity	The ability to see objects in the presence of a glare or bright lighting.
gross body coordination	The ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion.
gross body equilibrium	The ability to keep or regain your body balance or stay upright when in an unstable position.
hearing sensitivity	The ability to detect or tell the differences between sounds that vary in pitch and loudness.
manual dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
multilimb coordination	The ability to coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.
near vision	The ability to see details at close range (within a few feet of the observer).
night vision	The ability to see under low-light conditions.
peripheral vision	The ability to see objects or movement of objects to one's side when the eyes are looking ahead.
rate control	The ability to time your movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene.
reaction time	The ability to quickly respond (with the hand, finger, or foot) to a signal (sound, light, picture) when it appears.
response orientation	The ability to choose quickly between two or more movements in response to two or more different signals (lights, sounds, pictures). It includes the speed with which the correct response is started with the hand, foot, or other body part.
sound localisation	The ability to tell the direction from which a sound originated.
spatial orientation	The ability to know your location in relation to the environment or to know where other objects are in relation to you.
speed of limb movement	The ability to quickly move the arms and legs.
static strength	The ability to exert maximum muscle force to lift, push, pull, or carry objects.
trunk strength	The ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without "giving out" or fatiguing.
visual colour discrimination	The ability to match or detect differences between colours, including shades of colour and brightness.
wrist-finger speed	The ability to make fast, simple, repeated movements of the fingers, hands, and wrists.

Source: Own elaboration based on O*NET.

Table A2. The list of occupations, ISCO08 2-digits

ISCO-08 code	Occupation
11	Chief Executives, Senior Officials and Legislators
12	Administrative and Commercial Managers
13	Production and Specialized Services Managers
14	Hospitality, Retail and Other Services Managers
21	Science and Engineering Professionals
22	Health Professionals
23	Teaching Professionals
24	Business and Administration Professionals
25	Information and Communications Technology Professionals
26	Legal, Social and Cultural Professionals
31	Science and Engineering Associate Professionals
32	Health Associate Professionals
33	Business and Administration Associate Professionals
34	Legal, Social, Cultural and Related Associate Professionals
35	Information and Communications Technicians
41	General and Keyboard Clerks
42	Customer Services Clerks
43	Numerical and Material Recording Clerks
44	Other Clerical Support Workers
51	Personal Services Workers
52	Sales Workers
53	Personal Care Workers
54	Protective Services Workers
61	Market-oriented Skilled Agricultural Workers
62	Market-oriented Skilled Forestry, Fishery and Hunting Workers
63	Subsistence Farmers, Fishers, Hunters and Gatherers
71	Building and Related Trades Workers (excluding Electricians)
72	Metal, Machinery and Related Trades Workers
73	Handicraft and Printing Workers
74	Electrical and Electronic Trades Workers
75	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers
81	Stationary Plant and Machine Operators
82	Assemblers
83	Drivers and Mobile Plant Operators
91	Cleaners and Helpers
92	Agricultural, Forestry and Fishery Labourers
93	Labourers in Mining, Construction, Manufacturing and Transport
94	Food Preparation Assistants
95	Street and Related Sales and Services Workers
96	Refuse Workers and Other Elementary Workers

Source: own elaboration.

Table A3. Task items, corresponding questions and possible answers in PIAAC and STEP surveys

Task item	PIAAC		STEP	
	Question	Answers	Question	Answers
Changing order	Are you allowed to change the sequence of your tasks?	1. Not at all 2. Very little 3. To some extent 4. To a high extent 5. To a very high extent	Still thinking of your work [OCCUPATION] how much freedom do you have to decide how to do your work in your own way, rather than following a fixed procedure or a supervisor's instructions? Use any number from 1 to 10 where 1 is no freedom and 10 is complete freedom.	1-10
Complex problems	And how often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution? The 30 minutes only refers to the time needed to THINK of a solution, not the time needed to carry it out.	1. Never 2. Less than once a month 3. Less than once a week but at least once a month 4. At least once a week but not every day 5. Every day	Some tasks are pretty easy and can be done right away or after getting a little help from others. Other tasks require more thinking to figure out how they should be done. As part of this work as [OCCUPATIION], how often do you have to undertake tasks that require at least 30 minutes of thinking (examples: mechanic figuring out a car problem, budgeting for a business, teacher making a lesson plan, restaurant owner creating a new menu/dish for restaurant, dressmaker designing a new dress).	1. Never 2. Less than once a month 3. Less than once a week but at least once a month 4. At least once a week but not every day 5. Every day
Physical	How often are you usually working physically for a long period?	As above	Using any number from 1 to 10 where 1 is not at all physically demanding (such as sitting at desk answering telephone) and 10 is extremely physically demanding(such as carrying heavy loads, construction worker, etc.), what number would you use to rate how physically demanding your work is?	1-10
	In your job, how often are you usually…		As a regular part of this work, do you have to…	

Read news	reading articles in newspapers, magazines or newsletters?	As above	read newspapers or magazines?	Yes/ No
Read professional	reading articles in professional journals or scholarly publications?	As above	read reports?	As above
Fill forms	filling in forms?	As above	fill out bills or forms?	As above
Read manuals	reading manuals or reference materials?	As above	read instruction manuals/ operating manuals?	As above
Presenting	How often does your job usually involve making speeches or giving presentations in front of five or more people?	As above	As part of this work, do you have to make formal presentations to clients or collegues to provide information or persuade them of your point of view?	As above
	In your job, how often do you usually…		As a normal part of this work, do you do any of the following…?	
Use advanced math	use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques?	As above	use more advanced math, such as algebra, geometry, trigonometry, etc.	As above
Calculate prices	calculate prices, costs or budgets?	As above	calculate prices or costs	As above
Use programming	In your job, how often are you usually using a programming language to program or write computer code?	As above	Does your work as [OCCUPATION] require the use of software programming?	As above
Use email	In your job, how often do you usually use email?	As above	Does your work as [OCCUPATION] require the use email?	As above
Use spreadsheets	In your job, how often do you usually use spreadsheet software, for example Excel?	As above	Does your work as [OCCUPATION] require the use spreadsheets (such as Excel)?	As above
Supervising	Do you manage or supervise other employees?	As above	As a normal part of this work do you direct and check the work of other workers (supervise)?	As above
Time managing	How often does your job usually involve planning your own activities?	As above	N/A	
	How often does your job usually involve organising your own time?	As above		

Source: own elaboration based on PIAAC, STEP and CULS data.

Table A4. The full list of countries used in the study and data source

Country	Source	ISO 3166-1	Country	Source	ISO 3166-1
Armenia	STEP	AM	Kazakhstan	PIAAC	KZ
Austria	PIAAC	AT	Kenya	STEP	KE
Belgium	PIAAC	BE	Laos	STEP	LA
Bolivia	STEP	BO	Lithuania	PIAAC	LT
Canada	PIAAC	CA	Macedonia	STEP	MK
Chile	PIAAC	CL	Mexico	PIAAC	MX
China	CULS / STEP	CN	Netherlands	PIAAC	NL
Colombia	STEP	CO	New Zealand	PIAAC	NZ
Cyprus	PIAAC	CY	Norway	PIAAC	NO
Czechia	PIAAC	CZ	Peru	PIAAC	PE
Denmark	PIAAC	DK	Philippines	STEP	PH
Ecuador	PIAAC	EC	Poland	PIAAC	PL
Estonia	PIAAC	EE	Russia	PIAAC	RU
Finland	PIAAC	FI	Serbia	STEP	RS
France	PIAAC	FR	Singapore	PIAAC	SG
Georgia	STEP	GE	Slovakia	PIAAC	SK
Germany	PIAAC	DE	Slovenia	PIAAC	SI
Ghana	STEP	GH	South Korea	PIAAC	KR
Greece	PIAAC	GR	Spain	PIAAC	ES
Hungary	PIAAC	HU	Sri Lanka	STEP	LK
Indonesia	PIAAC	ID	Sweden	PIAAC	SE
Ireland	PIAAC	IE	Turkey	PIAAC	TR
Israel	PIAAC	IL	United Kingdom	PIAAC	UK
Italy	PIAAC	IT	United States	PIAAC	US
Japan	PIAAC	JP	Vietnam	STEP	VN

Source: own elaboration.

Table A5: Allocation of countries to income groups

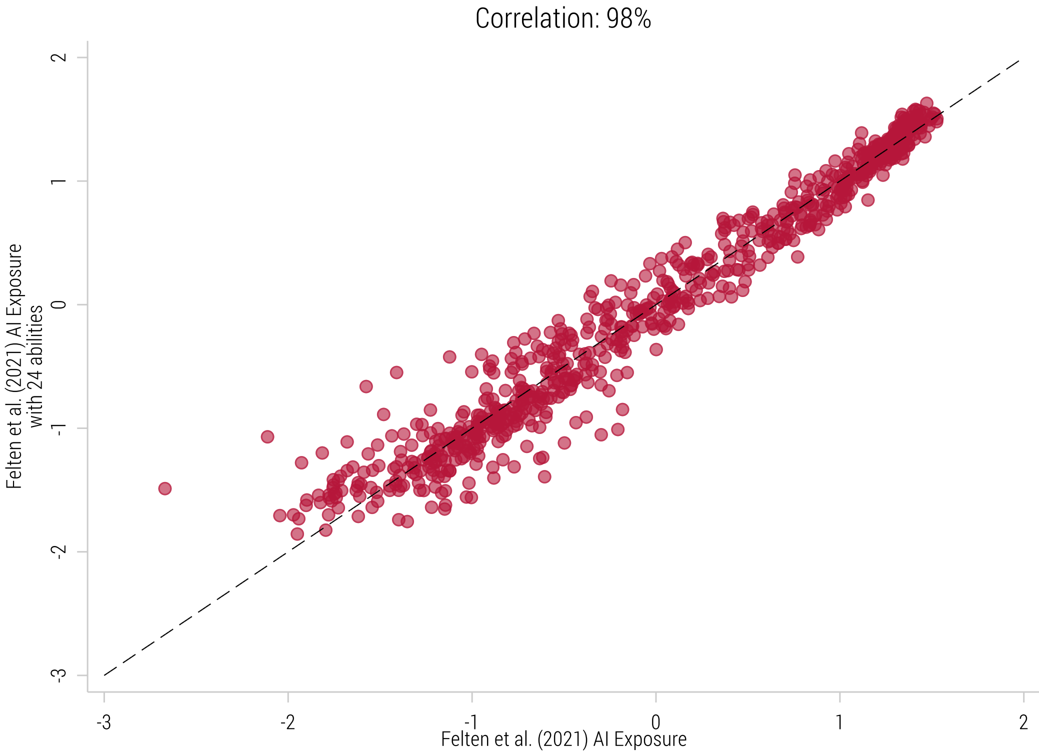
Low- and Lower Middle-Income	Upper Middle-Income	Lower-Tier High-Income	Upper-Tier High-Income
Covered by survey data			
Armenia	China	Chile	Austria
Bolivia	Colombia	Czechia	Belgium
Georgia	Ecuador	Cyprus	Canada
Ghana	Kazakhstan	Estonia	Denmark
Indonesia	Macedonia	Greece	Finland
Kenya	Mexico	Hungary	France
Laos	Peru	Italy	Germany
Philippines	Serbia	Lithuania	Ireland
Sri Lanka	Turkey	Poland	Israel
Vietnam		Russia	Japan
		Slovakia	Netherlands
		Slovenia	New Zealand
		South Korea	Norway
		Spain	Singapore
			Sweden
			United Kingdom
			United States
Covered by model-based predictions			
Bangladesh	Albania	Croatia	Australia
Cambodia	Azerbaijan	Latvia	Luxembourg
Cameroon	Belarus	Portugal	Switzerland
Egypt, Arab Rep.	Botswana	Uruguay	
El Salvador	Brazil		
Guatemala	Bulgaria		
Honduras	Dominican Republic		
India	Iran, Islamic Rep.		
Kyrgyz Republic	Jamaica		
Mongolia	Malaysia		
Morocco	Mauritius		
Pakistan	Namibia		
Paraguay	Romania		
Ukraine	South Africa		
Zambia	Thailand		

Notes: the allocation of countries to low- and lower middle-, upper middle-, and high-income groups follows the World Bank Analytical Classification. The additional split of high-income countries to the lower- and upper-tier subgroups follows Lewandowski et al. (2022). Table includes only countries with available employment data.

Source: authors' elaboration based on World Bank data.

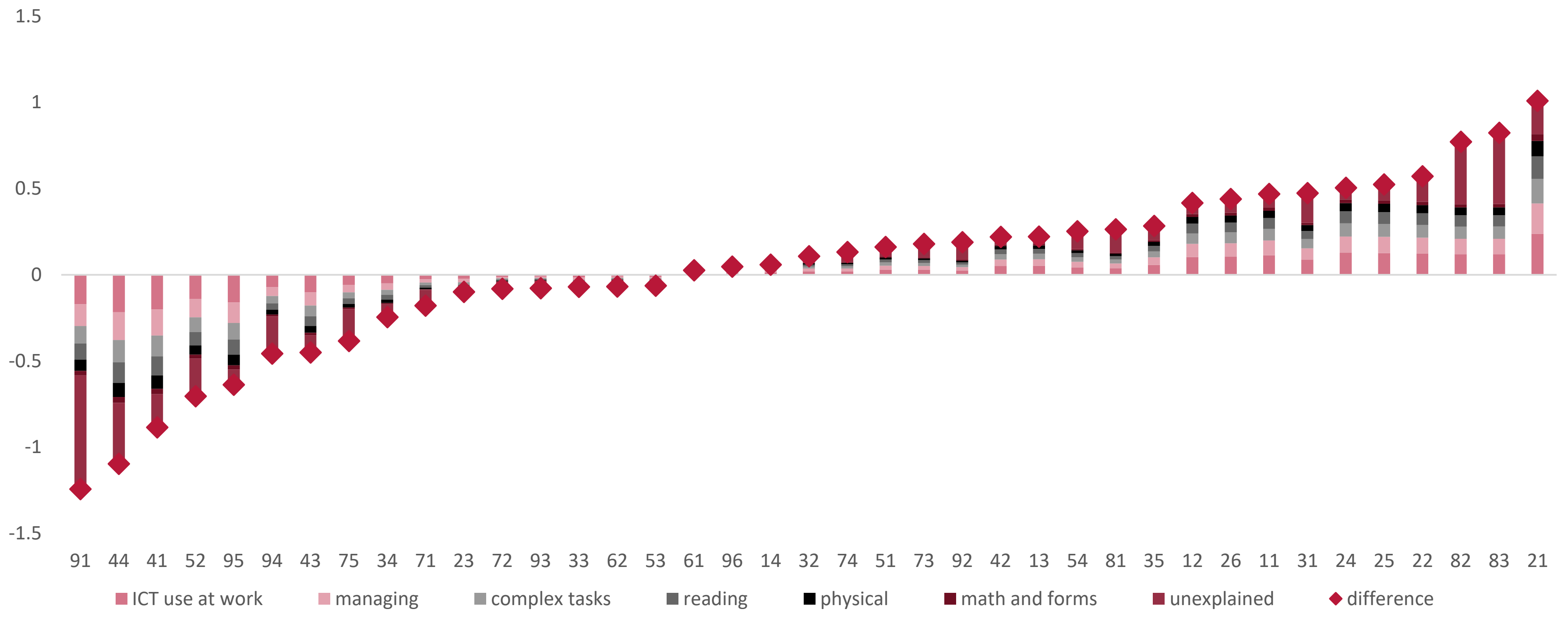
Appendix B – Additional results

Figure B1 . Correlation between AIOE and AIOE calculated on a restricted sample of abilities



Notes: 6-digit occupations in the SOC10 classification.
Source: own elaboration based on Felten et al. (2021)

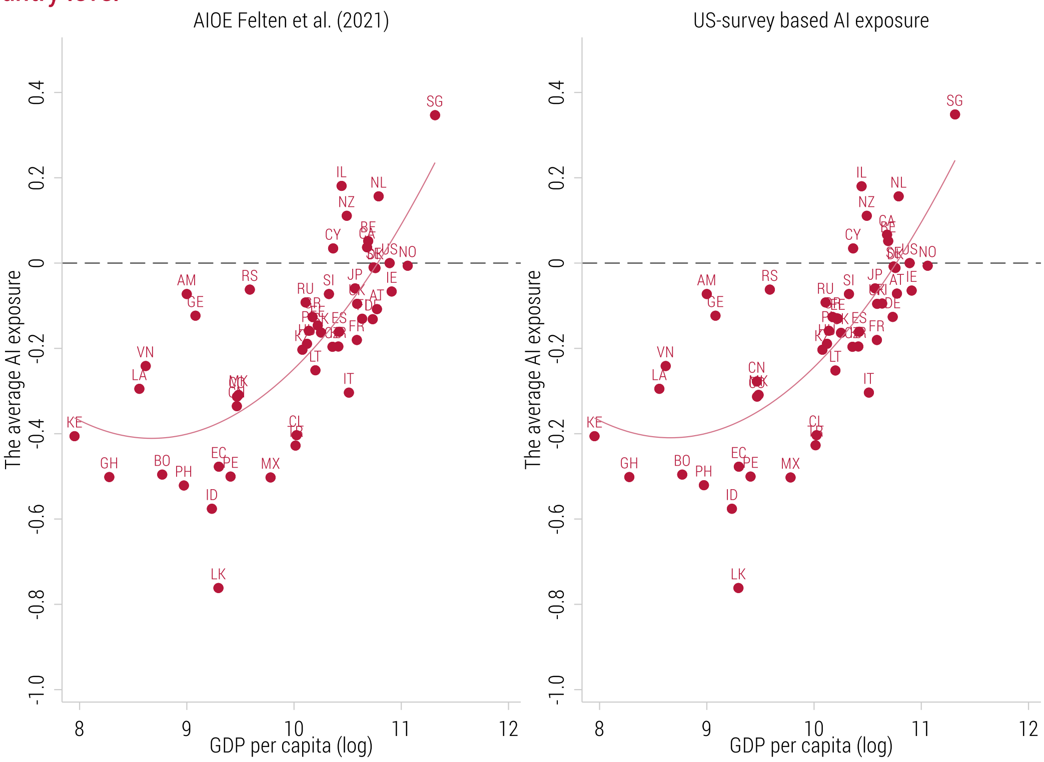
Figure B2. Decomposition of difference between Felten and PIAAC-based exposures, by PIAAC questions



Source: own elaboration based on PIAAC and O*NET data.

Note: : We use variance-covariance decomposition (Morduch and Sicular, 2002). The unexplained difference is the difference attributed to O*NET abilities that cannot be approximated with PIAAC. For the list of occupations, see Table A2 in the Appendix A.

Figure B3. The comparison of the average Felten et al. (2021) and the PIAAC-based US AI exposures at the country level



Note: AI exposures standardised with the US mean and standard deviation. Source: Own elaboration based on PIAAC, STEP, WB, EORA, ITU and CISCO data.

Within-country variance decomposition of worker-level AI exposure

This section assesses the importance of each question used in the study, decomposing a within-country variance in individual AI exposures. In other words, we calculate the share of variance in AI exposure explained by each question. Each question represents different skills required to perform occupations. We will refer to them as skill categories (see Table B1 for a list and corresponding questions).

Regarding PIAAC data, except *supervision* (dummy variable), each skill component takes values from 1 to 5 (categorical variable). See Table 1 for the list of questions used to approximate each ability required to perform each occupation.

In the case of STEP data, *physical*, *changing order* and *complex problems* take values from 1 to 5, and the rest are dummy variables (see Table 2 for the list of used questions). We use all available information (all skill components) to approximate each ability required to perform each occupation.

ICT use at work is the most important factor among PIAAC countries and explains, on average, 28% of the variance (see Figure B4). *Managing, solving complex problems* and *reading* explains 21%, 20% and 15% of the variance, respectively. *Physical* (9%) and *math and forms* (4%) skill categories are less important.

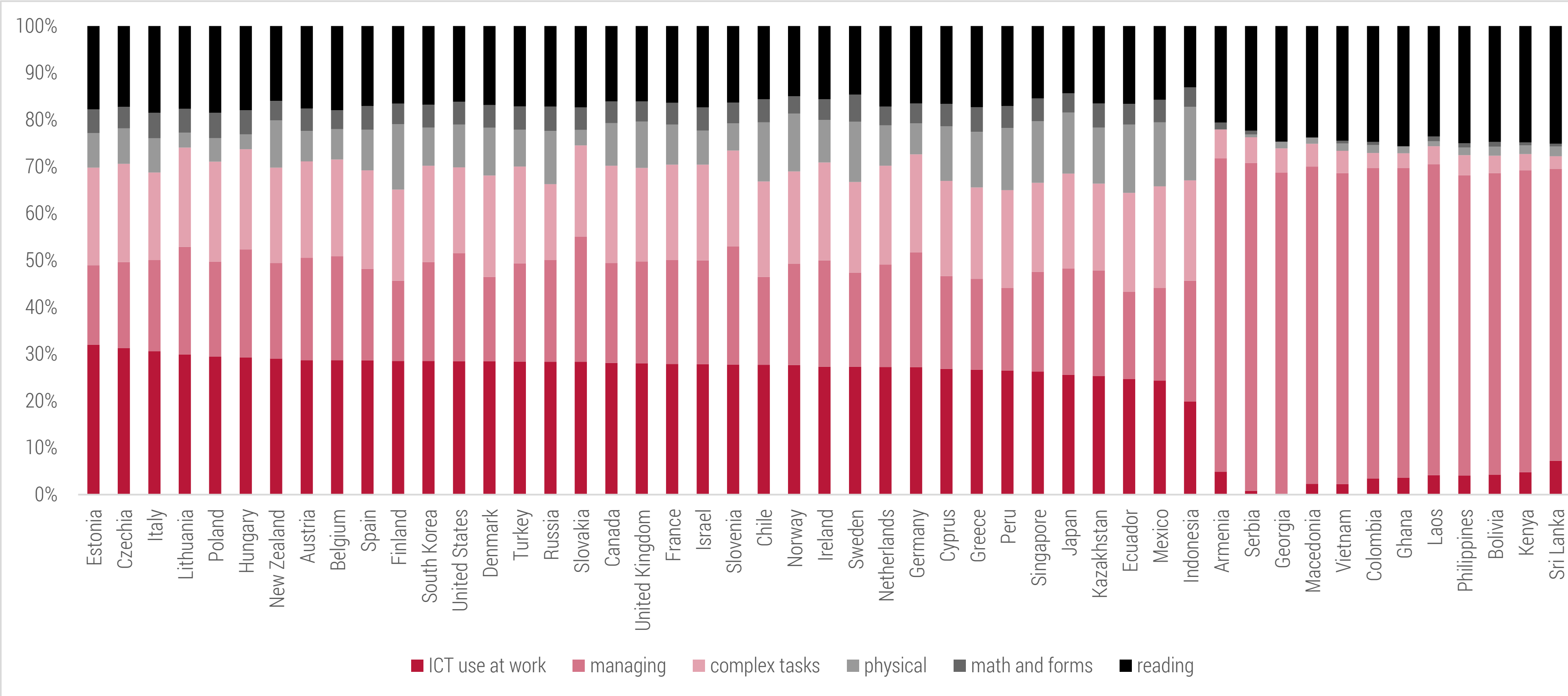
In the case of the STEP countries *managing* (161%) and *reading* (-59%) are the most important skill categories explaining the variance in the AI exposure. *Solving complex problems* (10%), *ICT use at work* (-7%), *physical* (-4%) *and math and forms* (-1%) are far less relevant,

Table B1. The list of questions used in the calculation of individual AI exposures, usage frequency and the share of explained within-country variance

Skill category	How many times used? (PIAAC)	Variance explained in US PIAAC (%)	Used in:	Question number	Complete question
ICT use at work	23	22.2%	PIAAC/ STEP	Q16	In your job, how often do you usually use email?
reading	22	18.3%	PIAAC/ STEP	Q7	And how often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution? The 30 minutes only refers to the time needed to THINK of a solution, not the time needed to carry it out.
reading	20	9.7%	PIAAC	Q5	How often does your job usually involve planning your own activities?
ICT use at work	20	9.1%	PIAAC/ STEP	Q8	How often does your job usually involve working physically for a long period?
physical	19	7.7%	PIAAC/ STEP	Q9	In your job, how often do you usually read articles in newspapers, magazines or newsletters?
managing	16	7.6%	PIAAC	Q6	How often does your job usually involve organising your own time?
complex tasks	14	6.2%	PIAAC/ STEP	Q17	In your job, how often do you usually use spreadsheet software, for example Excel?
managing	11	4.6%	PIAAC/ STEP	Q13	In your job, how often do you usually fill in forms?
managing	8	4.6%	PIAAC/ STEP	Q10	In your job, how often do you usually read articles in professional journals or scholarly publications?
reading	4	3.8%	PIAAC/ STEP	Q11	In your job, how often do you usually read manuals or reference materials?
math and forms	4	3.5%	PIAAC/ STEP	Q4	How often does your job usually involve making speeches or giving presentations in front of five or more people?
managing	2	2.0%	PIAAC/ STEP	Q3	In your job, what proportion of your time do you usually spend cooperating or collaborating with co-workers?
math and forms	2	0.2%	PIAAC/ STEP	Q1	Do you manage or supervise other employees?
managing	1	0.2%	PIAAC/ STEP	Q15	In your job, how often do you usually use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques?
reading	1	0.1%	PIAAC/ STEP	Q14	In your job, how often do you usually calculate prices, costs or budgets?
math and forms	1	0.1%	PIAAC/ STEP	Q18	In your job, how often do you usually use a programming language to program or write computer code?
ICT use at work	1	0.1%	PIAAC/ STEP	Q12	In your job, how often do you usually read bills, invoices, bank statements or other financial statements?
managing	0	0.0%	PIAAC/ STEP	Q2	To what extent can you choose or change the sequence of your tasks?

Source: Own elaboration based on PIAAC and STEP data.

Figure B4. Decomposition of within-country variance in AI exposure to skill categories



Notes: We use variance-covariance decomposition (Morduch and Sicular, 2002). For the list of task items and Its correspondence with the PIAAC/ STEP questions see Table A3 in the Appendix A. Countries sorted according to ICT use at work. Contributions of skill categories across STEP countries are rescaled to sum to 100%.
Source: own elaboration.

Regression results - PIAAC

Table B1. Estimation of the PIAAC question weights for O*NET abilities

VARIABLES	(1) auditory attention	(2) category flexibility	(3) deductive reasoning	(4) flexibility of closure	(5) fluency of ideas	(6) inductive reasoning
2.Q16	0.0505***	0.0319***	0.0464***	0.0187***	0.0392***	0.0566***
	(0.00585)	(0.00723)	(0.00970)	(0.00689)	(0.00769)	(0.00964)
3.Q16	0.0418***	0.0247***	0.0374***	0.0131*	0.0359***	0.0493***
	(0.00621)	(0.00770)	(0.0103)	(0.00733)	(0.00823)	(0.0103)
4.Q16	0.0401***	0.0348***	0.0548***	0.0245***	0.0433***	0.0658***
	(0.00377)	(0.00478)	(0.00642)	(0.00455)	(0.00508)	(0.00636)
5.Q16	0.0482***	0.0547***	0.0816***	0.0181***	0.0680***	0.0912***
	(0.00265)	(0.00381)	(0.00512)	(0.00358)	(0.00404)	(0.00506)
2.Q17	0.0172***	0.0112**	0.0181***	-0.00320	0.0111**	0.0135**
	(0.00403)	(0.00492)	(0.00661)	(0.00466)	(0.00527)	(0.00661)
3.Q17	0.0154***	0.0109**	0.0173***	-0.00219	0.0137***	0.0115*
	(0.00403)	(0.00494)	(0.00663)	(0.00468)	(0.00528)	(0.00662)
4.Q17	0.0160***	0.0158***	0.0228***	-0.00749*	0.0176***	0.0137**
	(0.00358)	(0.00443)	(0.00594)	(0.00417)	(0.00475)	(0.00595)
5.Q17	0.0196***	0.0231***	0.0295***	-0.00477	0.0216***	0.0195***
	(0.00302)	(0.00376)	(0.00504)	(0.00352)	(0.00402)	(0.00504)
2.Q10		0.00907**	0.0185***	0.00357	0.00743*	0.0161***
		(0.00375)	(0.00503)	(0.00358)	(0.00401)	(0.00502)
3.Q10		0.00954**	0.0244***	0.00261	0.0167***	0.0227***
		(0.00411)	(0.00552)	(0.00392)	(0.00442)	(0.00553)
4.Q10		0.0134***	0.0323***	0.00638	0.0209***	0.0310***
		(0.00410)	(0.00551)	(0.00392)	(0.00443)	(0.00555)
5.Q10		0.0105**	0.0250***	0.00502	0.0138**	0.0229***
		(0.00501)	(0.00673)	(0.00480)	(0.00540)	(0.00677)
2.Q9		0.0229***	0.0291***	0.0123***	0.0246***	0.0339***
		(0.00415)	(0.00557)	(0.00397)	(0.00442)	(0.00553)
3.Q9		0.0210***	0.0291***	0.0113***	0.0236***	0.0326***
		(0.00434)	(0.00582)	(0.00415)	(0.00463)	(0.00580)
4.Q9		0.0162***	0.0227***	0.00790**	0.0163***	0.0220***
		(0.00398)	(0.00534)	(0.00381)	(0.00425)	(0.00532)
5.Q9		0.0214***	0.0310***	0.00857**	0.0265***	0.0276***
		(0.00419)	(0.00562)	(0.00401)	(0.00447)	(0.00560)
2.Q8	0.0743***	0.0539***	0.0612***		0.0395***	0.0630***
	(0.00308)	(0.00393)	(0.00527)		(0.00418)	(0.00524)
3.Q8	0.0856***	0.0576***	0.0578***		0.0358***	0.0650***
	(0.00394)	(0.00497)	(0.00667)		(0.00529)	(0.00663)
4.Q8	0.100***	0.0533***	0.0511***		0.0290***	0.0597***
	(0.00292)	(0.00385)	(0.00517)		(0.00407)	(0.00510)
5.Q8	0.128***	0.0817***	0.0840***		0.0508***	0.0930***
	(0.00146)	(0.00241)	(0.00324)		(0.00250)	(0.00314)
2.Q7		0.0783***	0.0915***	0.0740***	0.0740***	0.101***
		(0.00358)	(0.00481)	(0.00338)	(0.00374)	(0.00469)

3.Q7		0.0709***	0.0845***	0.0706***	0.0672***	0.0930***
		(0.00374)	(0.00502)	(0.00354)	(0.00392)	(0.00491)
4.Q7		0.0781***	0.0962***	0.0777***	0.0747***	0.101***
		(0.00352)	(0.00472)	(0.00335)	(0.00371)	(0.00465)
5.Q7		0.0777***	0.0943***	0.0805***	0.0709***	0.0998***
		(0.00408)	(0.00547)	(0.00389)	(0.00433)	(0.00542)
2.Q5		0.0279***	0.0327***	0.0220***	0.0478***	0.0612***
		(0.00469)	(0.00629)	(0.00445)	(0.00468)	(0.00586)
3.Q5		0.0161***	0.0194***	0.0151***	0.0443***	0.0553***
		(0.00517)	(0.00693)	(0.00491)	(0.00514)	(0.00644)
4.Q5		0.0196***	0.0256***	0.0164***	0.0492***	0.0605***
		(0.00434)	(0.00583)	(0.00412)	(0.00419)	(0.00524)
5.Q5		0.0192***	0.0290***	0.0147***	0.0553***	0.0643***
		(0.00365)	(0.00489)	(0.00346)	(0.00317)	(0.00397)
2.Q6		0.0792***	0.0908***	0.0749***		
		(0.00602)	(0.00808)	(0.00567)		
3.Q6		0.0694***	0.0867***	0.0667***		
		(0.00603)	(0.00809)	(0.00569)		
4.Q6		0.0725***	0.0871***	0.0678***		
		(0.00495)	(0.00665)	(0.00468)		
5.Q6		0.0720***	0.0877***	0.0696***		
		(0.00376)	(0.00504)	(0.00351)		
2.Q11				0.0608***		
				(0.00331)		
3.Q11				0.0574***		
				(0.00354)		
4.Q11				0.0580***		
				(0.00361)		
5.Q11				0.0612***		
				(0.00351)		
2.Q4					0.0258***	0.0280***
					(0.00340)	(0.00426)
3.Q4					0.0287***	0.0267***
					(0.00419)	(0.00525)
4.Q4					0.0245***	0.0160***
					(0.00486)	(0.00609)
5.Q4					0.0338***	0.0311***
					(0.00451)	(0.00565)
Observations	4,726	4,719	4,719	4,723	4,717	4,717
R-squared	0.822	0.926	0.919	0.898	0.896	0.909

Notes: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B2. Estimation of the PIAAC question weights for O*NET abilities

VARIABLES	(7) information ordering	(8) mathematical reasoning	(9) memorisation	(10) number facility	(11) oral comprehension	(12) oral expression
2.Q16	0.0376***	0.0234***	0.0352***	0.0287***	0.0927***	0.0943***
	(0.00804)	(0.00666)	(0.00485)	(0.00670)	(0.0126)	(0.0127)
3.Q16	0.0283***	0.0210***	0.0297***	0.0320***	0.0796***	0.0815***
	(0.00856)	(0.00709)	(0.00517)	(0.00714)	(0.0134)	(0.0135)
4.Q16	0.0406***	0.0286***	0.0369***	0.0314***	0.0989***	0.101***
	(0.00532)	(0.00441)	(0.00319)	(0.00445)	(0.00828)	(0.00837)
5.Q16	0.0612***	0.0507***	0.0534***	0.0531***	0.139***	0.141***
	(0.00424)	(0.00351)	(0.00251)	(0.00342)	(0.00650)	(0.00657)
2.Q17	0.0126**	0.0182***	0.0123***	0.0184***	0.0277***	0.0304***
	(0.00548)	(0.00453)	(0.00333)	(0.00452)	(0.00862)	(0.00871)
3.Q17	0.0131**	0.0169***	0.0104***	0.0151***	0.0179**	0.0199**
	(0.00549)	(0.00455)	(0.00333)	(0.00463)	(0.00863)	(0.00872)
4.Q17	0.0178***	0.0327***	0.0136***	0.0356***	0.0278***	0.0297***
	(0.00493)	(0.00407)	(0.00298)	(0.00402)	(0.00773)	(0.00781)
5.Q17	0.0272***	0.0447***	0.0153***	0.0487***	0.0394***	0.0377***
	(0.00418)	(0.00346)	(0.00253)	(0.00338)	(0.00655)	(0.00662)
2.Q10	0.00948**	0.0127***	0.00834***	0.0100***	0.0186***	0.0180***
	(0.00417)	(0.00345)	(0.00252)	(0.00336)	(0.00654)	(0.00661)
3.Q10	0.00873*	0.0122***	0.0115***	0.0112***	0.0220***	0.0238***
	(0.00458)	(0.00379)	(0.00278)	(0.00373)	(0.00720)	(0.00728)
4.Q10	0.0153***	0.0158***	0.0127***	0.0153***	0.0234***	0.0241***
	(0.00456)	(0.00377)	(0.00279)	(0.00372)	(0.00722)	(0.00729)
5.Q10	0.00978*	0.0123***	0.00703**	0.00987**	0.0124	0.0122
	(0.00558)	(0.00461)	(0.00339)	(0.00450)	(0.00878)	(0.00888)
2.Q9	0.0253***	0.0173***	0.0266***	0.0245***	0.0783***	0.0780***
	(0.00462)	(0.00382)	(0.00275)	(0.00366)	(0.00713)	(0.00721)
3.Q9	0.0249***	0.0129***	0.0242***	0.0169***	0.0700***	0.0702***
	(0.00482)	(0.00399)	(0.00290)	(0.00388)	(0.00752)	(0.00760)
4.Q9	0.0190***	0.0101***	0.0195***	0.0134***	0.0579***	0.0595***
	(0.00442)	(0.00365)	(0.00267)	(0.00355)	(0.00692)	(0.00699)
5.Q9	0.0250***	0.0174***	0.0233***	0.0219***	0.0659***	0.0680***
	(0.00466)	(0.00384)	(0.00281)	(0.00371)	(0.00728)	(0.00735)
2.Q8	0.0636***	0.0265***	0.0410***	0.0296***	0.119***	0.113***
	(0.00437)	(0.00361)	(0.00261)	(0.00347)	(0.00676)	(0.00683)
3.Q8	0.0654***	0.0229***	0.0418***	0.0358***	0.129***	0.121***
	(0.00553)	(0.00458)	(0.00331)	(0.00463)	(0.00857)	(0.00866)
4.Q8	0.0629***	0.00898**	0.0419***	0.0219***	0.128***	0.118***
	(0.00428)	(0.00354)	(0.00252)	(0.00355)	(0.00652)	(0.00659)
5.Q8	0.0947***	0.0220***	0.0613***	0.0352***	0.181***	0.168***
	(0.00269)	(0.00222)	(0.00144)	(0.00217)	(0.00374)	(0.00378)
2.Q7	0.0868***	0.0466***		0.0552***		
	(0.00399)	(0.00328)		(0.00318)		
3.Q7	0.0805***	0.0474***		0.0584***		
	(0.00416)	(0.00342)		(0.00326)		
4.Q7	0.0891***	0.0572***		0.0666***		

	(0.00391)	(0.00321)		(0.00303)		
5.Q7	0.0899***	0.0542***		0.0635***		
	(0.00454)	(0.00373)		(0.00353)		
2.Q5	0.0298***		0.0450***		0.129***	0.124***
	(0.00521)		(0.00290)		(0.00751)	(0.00759)
3.Q5	0.0174***		0.0422***		0.117***	0.113***
	(0.00575)		(0.00318)		(0.00824)	(0.00833)
4.Q5	0.0200***		0.0429***		0.120***	0.116***
	(0.00483)		(0.00257)		(0.00667)	(0.00674)
5.Q5	0.0201***		0.0444***		0.119***	0.117***
	(0.00406)		(0.00193)		(0.00499)	(0.00505)
2.Q6	0.0874***	0.0467***				
	(0.00669)	(0.00532)				
3.Q6	0.0800***	0.0476***				
	(0.00670)	(0.00520)				
4.Q6	0.0829***	0.0494***				
	(0.00551)	(0.00423)				
5.Q6	0.0800***	0.0539***				
	(0.00418)	(0.00281)				
2.Q11						
3.Q11						
4.Q11						
5.Q11						
2.Q4			0.0147***		0.0314***	0.0329***
			(0.00214)		(0.00554)	(0.00560)
3.Q4			0.0147***		0.0312***	0.0333***
			(0.00263)		(0.00682)	(0.00689)
4.Q4			0.0123***		0.0198**	0.0235***
			(0.00305)		(0.00791)	(0.00800)
5.Q4			0.0310***		0.0520***	0.0729***
			(0.00284)		(0.00736)	(0.00744)
2.Q1				0.0330***		
				(0.00185)		
Observations	4,719	4,722	4,720	4,092	4,720	4,720
R-squared	0.928	0.871	0.900	0.889	0.906	0.902

Notes: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B3. Estimation of the PIAAC question weights for O*NET abilities

VARIABLES	(13) originality	(14) perceptual speed	(15) Problem sensitivity	(16) Selective attention	(17) Speech clarity	(18) Speech recognition
2.Q16	0.0461***	0.0202***	0.0530***	0.0411***	0.0755***	0.0565***
	(0.00796)	(0.00710)	(0.0111)	(0.00830)	(0.0104)	(0.0100)
3.Q16	0.0417***	0.0155**	0.0424***	0.0367***	0.0653***	0.0635***
	(0.00848)	(0.00746)	(0.0119)	(0.00871)	(0.0111)	(0.0106)
4.Q16	0.0496***	0.0159***	0.0604***	0.0321***	0.0795***	0.0613***
	(0.00524)	(0.00459)	(0.00736)	(0.00536)	(0.00687)	(0.00666)
5.Q16	0.0794***	-0.00119	0.0504***	0.0100***	0.111***	0.0950***
	(0.00412)	(0.00296)	(0.00581)	(0.00344)	(0.00540)	(0.00525)
2.Q17	0.0157***		-0.00634		0.0257***	0.0200***
	(0.00546)		(0.00756)		(0.00715)	(0.00683)
3.Q17	0.0173***		-0.00737		0.0178**	0.00977
	(0.00547)		(0.00759)		(0.00717)	(0.00686)
4.Q17	0.0216***		-0.0137**		0.0253***	0.0202***
	(0.00490)		(0.00677)		(0.00642)	(0.00615)
5.Q17	0.0239***		-0.00861		0.0287***	0.0313***
	(0.00415)		(0.00572)		(0.00543)	(0.00522)
2.Q10	0.0122***	0.00360	0.0184***	0.0168***	0.0115**	0.00539
	(0.00414)	(0.00344)	(0.00578)	(0.00397)	(0.00543)	(0.00519)
3.Q10	0.0223***	-0.00222	0.0187***	0.00956**	0.0168***	0.00402
	(0.00456)	(0.00371)	(0.00633)	(0.00428)	(0.00598)	(0.00572)
4.Q10	0.0264***	-0.000922	0.0290***	0.0137***	0.0154**	0.00645
	(0.00457)	(0.00353)	(0.00632)	(0.00403)	(0.00599)	(0.00572)
5.Q10	0.0165***	-0.000651	0.0258***	0.0151***	0.00493	0.00232
	(0.00556)	(0.00429)	(0.00773)	(0.00491)	(0.00729)	(0.00695)
2.Q9	0.0365***		0.0403***		0.0619***	0.0637***
	(0.00452)		(0.00639)		(0.00592)	(0.00565)
3.Q9	0.0329***		0.0466***		0.0563***	0.0590***
	(0.00476)		(0.00667)		(0.00624)	(0.00595)
4.Q9	0.0245***		0.0386***		0.0495***	0.0512***
	(0.00438)		(0.00611)		(0.00574)	(0.00546)
5.Q9	0.0345***		0.0400***		0.0567***	0.0577***
	(0.00461)		(0.00644)		(0.00604)	(0.00575)
2.Q8	0.0521***				0.0917***	0.0971***
	(0.00428)				(0.00561)	(0.00535)
3.Q8	0.0508***				0.0955***	0.109***
	(0.00543)				(0.00712)	(0.00677)
4.Q8	0.0469***				0.0940***	0.111***
	(0.00413)				(0.00541)	(0.00511)
5.Q8	0.0722***				0.134***	0.146***
	(0.00237)				(0.00310)	(0.00300)
2.Q7		0.0979***	0.138***	0.152***		
		(0.00331)	(0.00533)	(0.00365)		
3.Q7		0.0951***	0.133***	0.148***		
		(0.00348)	(0.00555)	(0.00382)		
4.Q7		0.0966***	0.144***	0.147***		

		(0.00332)	(0.00519)	(0.00360)		
5.Q7		0.100***	0.149***	0.149***		
		(0.00390)	(0.00605)	(0.00432)		
2.Q5	0.0637***		0.0448***		0.0973***	
	(0.00476)		(0.00721)		(0.00623)	
3.Q5	0.0646***		0.0289***		0.0893***	
	(0.00522)		(0.00796)		(0.00684)	
4.Q5	0.0679***		0.0289***		0.0909***	
	(0.00423)		(0.00669)		(0.00554)	
5.Q5	0.0721***		0.0301***		0.0930***	
	(0.00316)		(0.00562)		(0.00414)	
2.Q6			0.139***			
			(0.00916)			
3.Q6			0.127***			
			(0.00920)			
4.Q6			0.129***			
			(0.00752)			
5.Q6			0.131***			
			(0.00563)			
2.Q11		0.0682***				
		(0.00344)				
3.Q11		0.0620***				
		(0.00369)				
4.Q11		0.0630***				
		(0.00376)				
5.Q11		0.0622***				
		(0.00376)				
2.Q4	0.0311***				0.0250***	0.0210***
	(0.00351)				(0.00460)	(0.00439)
3.Q4	0.0336***				0.0273***	0.0250***
	(0.00432)				(0.00566)	(0.00540)
4.Q4	0.0301***				0.0234***	0.0145**
	(0.00501)				(0.00657)	(0.00626)
5.Q4	0.0420***				0.0770***	0.0260***
	(0.00466)				(0.00611)	(0.00581)
2.Q1						
2.Q13		0.0513***		0.0972***		0.113***
		(0.00396)		(0.00445)		(0.00540)
3.Q13		0.0453***		0.0879***		0.105***
		(0.00422)		(0.00477)		(0.00582)
4.Q13		0.0486***		0.0929***		0.104***
		(0.00390)		(0.00435)		(0.00532)
5.Q13		0.0578***		0.0997***		0.0959***
		(0.00321)		(0.00345)		(0.00431)
2.Q14		0.00695*				
		(0.00390)				
3.Q14		0.00741*				
		(0.00426)				
4.Q14		0.0114***				

		(0.00370)				
5.Q14		0.00163				
		(0.00261)				
Observations	4,720	4,727	4,723	4,727	4,720	4,722
R-squared	0.879	0.869	0.897	0.878	0.897	0.902

Notes: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B4. Estimation of the PIAAC question weights for O*NET abilities

VARIABLES	(19) speed of closure	(20) stamina	(21) timesharing	(22) visualisation	(23) written comprehension	(24) written expression
2.Q16	0.0244***	0.000378	0.0118**		0.0828***	0.0758***
	(0.00470)	(0.00538)	(0.00469)		(0.0116)	(0.0109)
3.Q16	0.0176***	-0.00813	0.0112**		0.0698***	0.0644***
	(0.00501)	(0.00573)	(0.00492)		(0.0123)	(0.0116)
4.Q16	0.0265***	-0.0115***	0.00745**		0.0931***	0.0862***
	(0.00311)	(0.00356)	(0.00305)		(0.00761)	(0.00718)
5.Q16	0.0348***	-0.0205***	-0.00283		0.137***	0.128***
	(0.00248)	(0.00282)	(0.00195)		(0.00598)	(0.00564)
2.Q17	0.00712**	-0.00614*			0.0309***	0.0294***
	(0.00320)	(0.00368)			(0.00792)	(0.00747)
3.Q17	0.00773**	-0.00604			0.0262***	0.0252***
	(0.00321)	(0.00369)			(0.00794)	(0.00749)
4.Q17	0.00816***	-0.0141***			0.0393***	0.0373***
	(0.00288)	(0.00330)			(0.00711)	(0.00670)
5.Q17	0.0125***	-0.0127***			0.0468***	0.0409***
	(0.00245)	(0.00281)			(0.00602)	(0.00568)
2.Q10	0.00894***	0.000191	-0.000214		0.0232***	0.0225***
	(0.00244)	(0.00279)	(0.00234)		(0.00602)	(0.00567)
3.Q10	0.0104***	-0.01000***	-0.000904		0.0330***	0.0343***
	(0.00268)	(0.00308)	(0.00260)		(0.00662)	(0.00625)
4.Q10	0.0151***	-0.00669**	0.00565**		0.0345***	0.0367***
	(0.00267)	(0.00308)	(0.00260)		(0.00664)	(0.00626)
5.Q10	0.0107***	-0.0104***	0.00292		0.0227***	0.0236***
	(0.00326)	(0.00375)	(0.00314)		(0.00808)	(0.00761)
2.Q9	0.0117***	0.00727**	0.00821***		0.0644***	0.0561***
	(0.00270)	(0.00307)	(0.00258)		(0.00656)	(0.00618)
3.Q9	0.0120***	0.00591*	0.00799***		0.0561***	0.0500***
	(0.00282)	(0.00322)	(0.00272)		(0.00691)	(0.00652)
4.Q9	0.00879***	0.00553*	0.00809***		0.0447***	0.0407***
	(0.00259)	(0.00296)	(0.00249)		(0.00636)	(0.00600)
5.Q9	0.0122***	0.00678**	0.00881***		0.0520***	0.0480***
	(0.00272)	(0.00311)	(0.00261)		(0.00669)	(0.00631)
2.Q8	0.0305***	0.0442***		0.0515***	0.0881***	0.0710***
	(0.00256)	(0.00291)		(0.00389)	(0.00621)	(0.00586)
3.Q8	0.0296***	0.0568***		0.0590***	0.0913***	0.0689***
	(0.00323)	(0.00369)		(0.00493)	(0.00788)	(0.00743)
4.Q8	0.0295***	0.0753***		0.0655***	0.0788***	0.0555***
	(0.00250)	(0.00283)		(0.00378)	(0.00599)	(0.00565)
5.Q8	0.0463***	0.0958***		0.0901***	0.119***	0.0886***
	(0.00157)	(0.00171)		(0.00227)	(0.00344)	(0.00324)
2.Q7	0.0444***		0.0332***	0.0774***		
	(0.00233)		(0.00230)	(0.00337)		
3.Q7	0.0431***		0.0282***	0.0775***		
	(0.00243)		(0.00238)	(0.00348)		
4.Q7	0.0486***		0.0301***	0.0856***		

	(0.00229)		(0.00225)	(0.00325)		
5.Q7	0.0482***		0.0291***	0.0866***		
	(0.00265)		(0.00259)	(0.00386)		
2.Q5	0.0146***	0.0144***			0.102***	0.0863***
	(0.00305)	(0.00348)			(0.00690)	(0.00651)
3.Q5	0.00831**	0.0138***			0.0964***	0.0828***
	(0.00336)	(0.00384)			(0.00758)	(0.00714)
4.Q5	0.00932***	0.0105***			0.102***	0.0898***
	(0.00283)	(0.00323)			(0.00613)	(0.00578)
5.Q5	0.00975***	0.00690**			0.105***	0.0945***
	(0.00237)	(0.00272)			(0.00459)	(0.00433)
2.Q6	0.0413***	0.0461***				
	(0.00392)	(0.00445)				
3.Q6	0.0388***	0.0331***				
	(0.00392)	(0.00444)				
4.Q6	0.0407***	0.0385***				
	(0.00322)	(0.00363)				
5.Q6	0.0399***	0.0298***				
	(0.00244)	(0.00274)				
2.Q11			0.0208***	0.0610***		
			(0.00233)	(0.00330)		
3.Q11			0.0168***	0.0556***		
			(0.00245)	(0.00352)		
4.Q11			0.0187***	0.0564***		
			(0.00249)	(0.00357)		
5.Q11			0.0176***	0.0591***		
			(0.00246)	(0.00352)		
2.Q4		-0.00598**			0.0346***	0.0345***
		(0.00237)			(0.00509)	(0.00480)
3.Q4		-0.00624**			0.0335***	0.0376***
		(0.00291)			(0.00627)	(0.00591)
4.Q4		-0.00678**			0.0257***	0.0324***
		(0.00338)			(0.00728)	(0.00686)
5.Q4		-0.0195***			0.0626***	0.0757***
		(0.00314)			(0.00677)	(0.00638)
2.Q1			0.0355***			
			(0.00136)			
2.Q13			0.0223***			
			(0.00261)			
3.Q13			0.0246***			
			(0.00276)			
4.Q13			0.0249***			
			(0.00254)			
5.Q13			0.0295***			
			(0.00208)			
2.Q14				0.00810**		
				(0.00405)		
3.Q14				0.00876**		
				(0.00445)		
4.Q14				0.00673*		

				(0.00399)		
5.Q14				-0.00708**		
				(0.00300)		
2.Q3			0.0852***			
			(0.00259)			
3.Q3			0.0896***			
			(0.00278)			
4.Q3			0.0954***			
			(0.00251)			
5.Q3			0.102***			
			(0.00207)			
2.Q15				0.0150***		
				(0.00419)		
3.Q15				0.0214***		
				(0.00585)		
4.Q15				0.0233***		
				(0.00594)		
5.Q15				0.0203***		
				(0.00640)		
2.Q18				0.00889		
				(0.00607)		
3.Q18				0.0302***		
				(0.00886)		
4.Q18				0.0147*		
				(0.00775)		
5.Q18				0.0318***		
				(0.00589)		
2.Q12				0.00988**		
				(0.00423)		
3.Q12				0.0152***		
				(0.00409)		
4.Q12				0.00840**		
				(0.00368)		
5.Q12				-0.00495		
				(0.00339)		
Observations	4,719	4,719	4,094	4,721	4,720	4,720
R-squared	0.912	0.723	0.948	0.870	0.897	0.887

Notes: Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Regression results – STEP

Table B5. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(1) auditory attention	(2) category flexibility	(3) deductive reasoning	(4) flexibility of closure	(5) fluency of ideas	(6) inductive reasoning
Physical: 3-4	0.00727***	-0.00800***	-0.0138***	-0.00335	-0.0161***	-0.0117***
	(0.00210)	(0.00219)	(0.00367)	(0.00244)	(0.00325)	(0.00378)
5-6	0.00766***	-0.0105***	-0.0232***	-0.00407	-0.0260***	-0.0195***
	(0.00265)	(0.00276)	(0.00463)	(0.00308)	(0.00409)	(0.00477)
7-8	0.0174***	-0.0206***	-0.0371***	-0.00706***	-0.0388***	-0.0322***
	(0.00208)	(0.00216)	(0.00362)	(0.00241)	(0.00321)	(0.00374)
9-10	0.0235***	-0.0203***	-0.0378***	-0.00525***	-0.0409***	-0.0325***
	(0.00153)	(0.00159)	(0.00267)	(0.00178)	(0.00236)	(0.00275)
Use email: No	0.00877***	-0.0228***	-0.0425***	-0.0200***	-0.0300***	-0.0455***
	(0.00194)	(0.00202)	(0.00339)	(0.00226)	(0.00300)	(0.00350)
Use computer: No	0.00619***	0.00164	0.00163	0.00738***	-0.00577**	0.00156
	(0.00188)	(0.00196)	(0.00328)	(0.00219)	(0.00291)	(0.00339)
Presenting: No	0.113***	0.308***	0.408***	0.239***	0.301***	0.374***
	(0.00310)	(0.00322)	(0.00541)	(0.00360)	(0.00479)	(0.00558)
Presenting reversed: No	0.105***	0.319***	0.433***	0.243***	0.328***	0.399***
	(0.00292)	(0.00303)	(0.00509)	(0.00339)	(0.00450)	(0.00525)
Changing order: Very little	0.000784	-0.00359**	-0.00637**	-0.00165	-0.00866***	-0.00378
	(0.00171)	(0.00178)	(0.00298)	(0.00199)	(0.00264)	(0.00308)
To some extent	0.00329**	-0.00549***	-0.00823***	-0.00276	-0.0101***	-0.00485*
	(0.00158)	(0.00164)	(0.00276)	(0.00184)	(0.00244)	(0.00284)
To high extent	0.00446**	-0.00714***	-0.00975***	-0.00391*	-0.0124***	-0.00616*
	(0.00201)	(0.00209)	(0.00351)	(0.00234)	(0.00311)	(0.00362)
To very high extent	0.0116***	-0.00402*	-0.00664*	0.00213	-0.0106***	-0.00325
	(0.00228)	(0.00237)	(0.00398)	(0.00265)	(0.00352)	(0.00411)
Read news: No	0.000809	-0.00169	-0.00735***	-0.000546	-0.00714***	-0.00694**
	(0.00152)	(0.00158)	(0.00265)	(0.00177)	(0.00235)	(0.00274)
Read professional: No	0.000116	-0.0129***	-0.0243***	-0.0124***	-0.0211***	-0.0261***
	(0.00153)	(0.00159)	(0.00267)	(0.00178)	(0.00236)	(0.00275)
Use spreadsheets: No	0.00675***	-0.00626***	-0.00741***	-0.000491	-0.00716***	-0.000868
	(0.00156)	(0.00162)	(0.00272)	(0.00181)	(0.00241)	(0.00281)
Use programming: No	-0.00137	-0.00999***	-0.00838**	-0.0124***	-0.00998***	-0.00595*
	(0.00192)	(0.00200)	(0.00335)	(0.00223)	(0.00297)	(0.00346)
Supervising: No	-0.000180	-0.00887***	-0.0221***	-0.00764***	-0.0207***	-0.0180***
	(0.00137)	(0.00143)	(0.00239)	(0.00159)	(0.00212)	(0.00247)

Complex problems: Less than once a month	0.00479**	0.00849***	0.0112***	0.00900***	0.00841***	0.0113***
	(0.00193)	(0.00201)	(0.00337)	(0.00225)	(0.00299)	(0.00348)
Less than once a week but at least once a month	0.00826***	0.0104***	0.0141***	0.0129***	0.00964***	0.0134***
	(0.00199)	(0.00207)	(0.00347)	(0.00231)	(0.00307)	(0.00358)
A least once a week but not every day	0.0111***	0.0151***	0.0216***	0.0182***	0.0172***	0.0211***
	(0.00190)	(0.00198)	(0.00332)	(0.00221)	(0.00294)	(0.00342)
Every day	0.0107***	0.0154***	0.0198***	0.0189***	0.0145***	0.0213***
	(0.00218)	(0.00227)	(0.00381)	(0.00254)	(0.00337)	(0.00393)
Fill forms: No	-0.00644***	-0.00190	-0.00616***	-0.00567***	0.00217	-0.00798***
	(0.00132)	(0.00137)	(0.00230)	(0.00153)	(0.00204)	(0.00237)
Observations	4,712	4,712	4,712	4,712	4,712	4,712
R-squared	0.930	0.979	0.963	0.959	0.942	0.956

Notes: Standard errors in parentheses. See Table A3 for questions associated with task items.
*** p<0.01, ** p<0.05, * p<0.1

Table B6. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(7) information ordering	(8) mathematical reasoning	(9) memorisation	(10) number facility	(11) oral comprehension	(12) oral expression
Physical: 3-4	-0.00659***	-0.0119***	-0.00662***	-0.0115***	-0.0145***	-0.0166***
	(0.00233)	(0.00320)	(0.00163)	(0.00269)	(0.00338)	(0.00387)
5-6	-0.0115***	-0.0178***	-0.0126***	-0.0172***	-0.0236***	-0.0278***
	(0.00294)	(0.00404)	(0.00205)	(0.00340)	(0.00426)	(0.00488)
7-8	-0.0205***	-0.0359***	-0.0171***	-0.0311***	-0.0378***	-0.0432***
	(0.00230)	(0.00316)	(0.00161)	(0.00266)	(0.00333)	(0.00382)
9-10	-0.0205***	-0.0389***	-0.0175***	-0.0330***	-0.0406***	-0.0468***
	(0.00170)	(0.00233)	(0.00118)	(0.00196)	(0.00246)	(0.00282)
Use email: No	-0.0244***	-0.0263***	-0.0158***	-0.0190***	-0.0383***	-0.0414***
	(0.00215)	(0.00296)	(0.00150)	(0.00249)	(0.00312)	(0.00358)
Use computer: No	0.00127	-0.00567**	-0.00658***	-0.00675***	-0.0126***	-0.0169***
	(0.00209)	(0.00287)	(0.00146)	(0.00241)	(0.00302)	(0.00347)
Presenting: No	0.353***	0.254***	0.176***	0.241***	0.469***	0.462***
	(0.00344)	(0.00472)	(0.00240)	(0.00397)	(0.00498)	(0.00571)
Presenting reversed: No	0.363***	0.266***	0.190***	0.249***	0.493***	0.494***
	(0.00323)	(0.00445)	(0.00226)	(0.00374)	(0.00469)	(0.00537)
Changing order: Very little	-0.00394**	-0.00701***	-0.00141	-0.00625***	-0.00253	-0.00311

	(0.00190)	(0.00261)	(0.00132)	(0.00219)	(0.00275)	(0.00315)
To some extent	-0.00562***	-0.00912***	0.000432	-0.00805***	-0.000734	0.000433
	(0.00175)	(0.00241)	(0.00122)	(0.00203)	(0.00254)	(0.00291)
To high extent	-0.00734***	-0.0100***	-0.000391	-0.00819***	-0.00239	-0.000441
	(0.00223)	(0.00307)	(0.00156)	(0.00258)	(0.00323)	(0.00371)
To very high extent	-0.00437*	-0.00833**	0.00162	-0.00730**	-0.00222	0.000197
	(0.00253)	(0.00348)	(0.00176)	(0.00292)	(0.00366)	(0.00420)
Read news: No	-0.00254	-0.00213	-0.00379***	-0.00179	-0.00963***	-0.0119***
	(0.00169)	(0.00232)	(0.00118)	(0.00195)	(0.00244)	(0.00280)
Read professional: No	-0.0134***	-0.00934***	-0.0101***	-0.00607***	-0.0206***	-0.0225***
	(0.00170)	(0.00233)	(0.00118)	(0.00196)	(0.00246)	(0.00282)
Use spreadsheets: No	-0.00614***	-0.0228***	-0.00122	-0.0195***	-0.000308	-0.000522
	(0.00173)	(0.00238)	(0.00121)	(0.00200)	(0.00251)	(0.00288)
Use programming: No	-0.0164***	-0.0179***	0.000600	-0.0122***	0.00634**	0.0134***
	(0.00213)	(0.00293)	(0.00149)	(0.00246)	(0.00309)	(0.00354)
Supervising: No	-0.0128***	-0.0214***	-0.00832***	-0.0200***	-0.0152***	-0.0159***
	(0.00152)	(0.00209)	(0.00106)	(0.00176)	(0.00220)	(0.00253)
Complex problems: Less than once a month	0.00735***	0.00732**	0.00529***	0.00531**	0.00938***	0.00989***
	(0.00214)	(0.00295)	(0.00150)	(0.00248)	(0.00311)	(0.00356)
Less than once a week but at least once a month	0.0116***	0.0130***	0.00561***	0.0109***	0.00855***	0.00804**
	(0.00220)	(0.00303)	(0.00154)	(0.00255)	(0.00319)	(0.00366)
A least once a week but not every day	0.0170***	0.0199***	0.00860***	0.0164***	0.0107***	0.0101***
	(0.00211)	(0.00290)	(0.00147)	(0.00244)	(0.00306)	(0.00350)
Every day	0.0182***	0.0162***	0.00661***	0.0124***	0.00857**	0.00516
	(0.00242)	(0.00333)	(0.00169)	(0.00280)	(0.00351)	(0.00402)
Fill forms: No	-0.00356**	-0.00546***	-0.00288***	-0.00500***	-0.00958***	-0.0109***
	(0.00146)	(0.00201)	(0.00102)	(0.00169)	(0.00212)	(0.00243)
Observations	4,712	4,712	4,712	4,712	4,712	4,712
R-squared	0.981	0.906	0.965	0.930	0.979	0.971

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Table A3 for questions associated with task items.

Table B7. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(13) originality	(14) perceptual speed	(15) problem sensitivity	(16) selective attention	(17) speech clarity	(18) speech recognition
Physical: 3-4	(13)	(14)	(15)	(16)	(17)	(18)
	scalar	scalar	scalar	scalar	scalar	scalar
5-6						
	-0.0146***	0.00128	-0.00658*	-0.000235	-0.0128***	-0.0109***
7-8	(0.00330)	(0.00230)	(0.00375)	(0.00151)	(0.00334)	(0.00239)
	-0.0234***	0.000575	-0.0143***	-0.00183	-0.0252***	-0.0201***
9-10	(0.00416)	(0.00290)	(0.00474)	(0.00191)	(0.00421)	(0.00302)
	-0.0349***	0.000955	-0.0200***	-0.00192	-0.0358***	-0.0310***
Use email: No	(0.00326)	(0.00227)	(0.00371)	(0.00150)	(0.00329)	(0.00237)
	-0.0365***	0.00507***	-0.0164***	-3.58e-05	-0.0383***	-0.0339***
Use computer: No	(0.00240)	(0.00168)	(0.00273)	(0.00110)	(0.00243)	(0.00174)
	-0.0275***	-0.0101***	-0.0369***	-0.00857***	-0.0302***	-0.0218***
Presenting: No	(0.00305)	(0.00213)	(0.00347)	(0.00140)	(0.00308)	(0.00221)
	-0.00702**	0.00931***	0.00344	0.000567	-0.0158***	-0.0171***
Presenting reversed: No	(0.00296)	(0.00206)	(0.00336)	(0.00136)	(0.00299)	(0.00215)
	0.285***	0.207***	0.399***	0.250***	0.359***	0.367***
Changing order: Very little	(0.00487)	(0.00339)	(0.00554)	(0.00223)	(0.00492)	(0.00353)
	0.314***	0.202***	0.415***	0.252***	0.389***	0.379***
To some extent	(0.00458)	(0.00319)	(0.00521)	(0.00210)	(0.00463)	(0.00332)
	-0.00857***	-0.000176	-0.00495	-9.47e-05	-0.00292	-0.00317
To high extent	(0.00269)	(0.00187)	(0.00306)	(0.00123)	(0.00272)	(0.00195)
	-0.00909***	-0.000385	-0.00597**	0.00196*	0.00212	-0.00172
To very high extent	(0.00248)	(0.00173)	(0.00282)	(0.00114)	(0.00251)	(0.00180)
	-0.0116***	-0.000862	-0.00677*	0.00198	0.00226	-0.000726
Read news: No	(0.00316)	(0.00221)	(0.00360)	(0.00145)	(0.00320)	(0.00229)
	-0.0103***	0.00603**	-0.00309	0.00698***	0.00352	-0.00226
Read professional: No	(0.00358)	(0.00250)	(0.00407)	(0.00164)	(0.00362)	(0.00260)
	-0.00693***	0.00137	-0.00747***	-0.000877	-0.0104***	-0.00725***
Use spreadsheets: No	(0.00239)	(0.00166)	(0.00272)	(0.00110)	(0.00241)	(0.00173)
	-0.0212***	-0.00626***	-0.0241***	-0.00572***	-0.0177***	-0.0101***
Use programming: No	(0.00240)	(0.00167)	(0.00273)	(0.00110)	(0.00243)	(0.00174)
	-0.00485**	-0.00108	0.00479*	0.00213*	-0.000689	-0.00245
Supervising: No	(0.00245)	(0.00171)	(0.00279)	(0.00112)	(0.00248)	(0.00178)
	-0.00984***	-0.0114***	-0.00580*	-0.00530***	0.0207***	0.0139***
Complex problems: Less	(0.00302)	(0.00210)	(0.00343)	(0.00138)	(0.00305)	(0.00219)

than once a month						
	-0.0208***	-0.00402***	-0.0235***	-0.00355***	-0.0138***	-0.0165***
Less than once a week but at least once a month	(0.00215)	(0.00150)	(0.00245)	(0.000988)	(0.00218)	(0.00156)
	0.00760**	0.00678***	0.00952***	0.00467***	0.00756**	0.00269
A least once a week but not every day	(0.00304)	(0.00212)	(0.00345)	(0.00139)	(0.00307)	(0.00220)
	0.00835***	0.0119***	0.0123***	0.00808***	0.00431	0.00249
Every day	(0.00312)	(0.00218)	(0.00355)	(0.00143)	(0.00315)	(0.00226)
	0.0163***	0.0153***	0.0188***	0.0106***	0.00496	0.00176
Fill forms: No	(0.00299)	(0.00208)	(0.00340)	(0.00137)	(0.00302)	(0.00217)
	0.0129***	0.0166***	0.0197***	0.0111***	-0.000258	0.000294
	(0.00343)	(0.00239)	(0.00390)	(0.00157)	(0.00346)	(0.00249)
Observations	0.00375*	-0.00818***	-0.0104***	-0.00609***	-0.00729***	-0.00824***
R-squared	(0.00207)	(0.00144)	(0.00236)	(0.000951)	(0.00209)	(0.00150)

Notes: Standard errors in parentheses. See Table A3 for questions associated with task items. *** p<0.01, ** p<0.05, * p<0.1

Table B8. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(19) speed of closure	(20) stamina	(21) timesharing	(22) visualisation	(23) written comprehension	(24) written expression
Physical: 3-4	-0.00474***	0.0147***	0.00225*	0.00307	-0.0188***	-0.0201***
	(0.00181)	(0.00257)	(0.00134)	(0.00309)	(0.00431)	(0.00458)
5-6	-0.00896***	0.0237***	0.000189	0.00585	-0.0309***	-0.0351***
	(0.00228)	(0.00324)	(0.00169)	(0.00390)	(0.00544)	(0.00578)
7-8	-0.0122***	0.0404***	0.00269**	0.0102***	-0.0543***	-0.0576***
	(0.00179)	(0.00253)	(0.00132)	(0.00305)	(0.00426)	(0.00452)
9-10	-0.0116***	0.0480***	0.00557***	0.0177***	-0.0581***	-0.0623***
	(0.00132)	(0.00187)	(0.000976)	(0.00225)	(0.00314)	(0.00333)
Use email: No	-0.0171***	0.0222***	-0.00150	-0.00264	-0.0542***	-0.0550***
	(0.00167)	(0.00237)	(0.00124)	(0.00286)	(0.00399)	(0.00423)
Use computer: No	0.00147	0.0205***	-0.00326***	0.0166***	-0.00909**	-0.0105**
	(0.00162)	(0.00230)	(0.00120)	(0.00277)	(0.00386)	(0.00410)
Presenting: No	0.187***	0.0169***	0.187***	0.194***	0.437***	0.399***
	(0.00267)	(0.00378)	(0.00198)	(0.00456)	(0.00636)	(0.00675)
Presenting reversed: No	0.192***	0.00655*	0.189***	0.194***	0.469***	0.436***
	(0.00251)	(0.00356)	(0.00186)	(0.00429)	(0.00598)	(0.00636)
Changing order: Very little	-0.00189	0.00271	-0.00107	-0.00450*	-0.00494	-0.00670*
	(0.00147)	(0.00209)	(0.00109)	(0.00252)	(0.00351)	(0.00373)
To some extent	-0.00183	0.00319*	0.00147	-0.00555**	-0.00520	-0.00612*

	(0.00136)	(0.00193)	(0.00101)	(0.00232)	(0.00324)	(0.00344)
To high extent	-0.00225	0.00300	0.00199	-0.00740**	-0.00735*	-0.00818*
	(0.00173)	(0.00246)	(0.00128)	(0.00296)	(0.00413)	(0.00439)
To very high extent	0.000659	0.00534*	0.00419***	0.000402	-0.00518	-0.00585
	(0.00196)	(0.00278)	(0.00146)	(0.00335)	(0.00468)	(0.00497)
Read news: No	-0.00217*	0.00397**	-0.00298***	0.00313	-0.00934***	-0.0118***
	(0.00131)	(0.00186)	(0.000970)	(0.00224)	(0.00312)	(0.00331)
Read professional: No	-0.0110***	0.00557***	-0.00456***	-0.00866***	-0.0269***	-0.0288***
	(0.00132)	(0.00187)	(0.000976)	(0.00225)	(0.00314)	(0.00333)
Use spreadsheets: No	-0.00159	0.0140***	0.00575***	0.00286	-0.0131***	-0.0128***
	(0.00134)	(0.00191)	(0.000996)	(0.00230)	(0.00320)	(0.00340)
Use programming: No	-0.00603***	0.00431*	0.00456***	-0.0224***	0.00116	0.00603
	(0.00165)	(0.00235)	(0.00123)	(0.00283)	(0.00394)	(0.00419)
Supervising: No	-0.0110***	0.00905***	-0.00858***	-0.00310	-0.0193***	-0.0239***
	(0.00118)	(0.00167)	(0.000875)	(0.00202)	(0.00281)	(0.00299)
Complex problems: Less than once a month	0.00537***	-9.34e-05	0.00143	0.0100***	0.0137***	0.0142***
	(0.00167)	(0.00236)	(0.00123)	(0.00284)	(0.00397)	(0.00421)
Less than once a week but at least once a month	0.00875***	-0.00244	0.00250**	0.0156***	0.0156***	0.0145***
	(0.00171)	(0.00243)	(0.00127)	(0.00292)	(0.00408)	(0.00433)
A least once a week but not every day	0.0124***	-0.00214	0.00315***	0.0249***	0.0198***	0.0187***
	(0.00164)	(0.00232)	(0.00121)	(0.00280)	(0.00390)	(0.00414)
Every day	0.0120***	-0.00135	0.00170	0.0258***	0.0170***	0.0145***
	(0.00188)	(0.00266)	(0.00139)	(0.00321)	(0.00448)	(0.00475)
Fill forms: No	-0.00458***	0.00593***	-0.00604***	0.00120	-0.0109***	-0.0100***
	(0.00114)	(0.00161)	(0.000841)	(0.00194)	(0.00270)	(0.00287)
Observations	4,712	4,712	4,712	4,712	4,712	4,712
R-squared	0.959	0.801	0.983	0.923	0.955	0.937

Notes: Standard errors in parentheses See Table A3 for questions associated with task items. *** p<0.01, ** p<0.05, * p<0.1

Regression results – out-of-sample predictions

Table B9. Estimation of the out-of-sample prediction models

VARIABLES	(1) ISCO 1	(2) ISCO 2	(3) ISCO 3	(4) ISCO 4	(5) ISCO 5	(6) ISCO 7	(7) ISCO 8	(8) ISCO 9
log GDP pc	0.053	0.229*	-1.250	0.010	-0.093	0.140	0.092	-0.112
	(0.085)	(0.133)	(1.010)	(0.137)	(0.148)	(0.106)	(0.093)	(0.128)
log GDP pc squared			0.078					
			(0.049)					
Learning-Adjusted Years of School	0.076**		0.108***					
	(0.029)		(0.036)					
Urbanisation rate	0.004*	0.006**						
	(0.002)	(0.003)						
Share of population	0.004			0.010*	0.012**	0.009**	0.010***	0.016***
with access to internet	(0.003)			(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Human Capital Index		1.362*						
(HCI) (scale 0-1)		(0.722)						
IDI 2017 Value		-0.090	-0.038				-0.131**	-0.308***
		(0.060)	(0.053)				(0.064)	(0.101)
Technology Adoption			-0.112					
			(0.072)					
University enrolment				0.003				
				(0.002)				
ICT Development Index				-0.245**	-0.194*	-0.137		
				(0.103)	(0.099)	(0.083)		
OverallDRIScore				0.243**		0.201**		
				(0.109)		(0.098)		
Forward GVC participation				0.729				1.041*
				(0.589)				(0.561)
Share of population with electricity					-0.008*	-0.004	-0.004	
					(0.005)	(0.003)	(0.003)	
Technology Infrastructure					0.206**			
					(0.081)			
(ARMT) survival rate					3.027**			
from age 15-60					(1.186)			
ICT import						-0.010*		-0.017**
						(0.006)		(0.007)
Technology Infrastructure							0.131**	
							(0.052)	
Backward GVC							-0.627***	
participation							(0.186)	
Overall DRI Score								0.363***
								(0.115)
Constant	-1.822***	-3.105***	3.640	0.862	-0.944	-1.761**	-1.543**	0.911
	(0.631)	(0.927)	(5.063)	(1.125)	(1.227)	(0.842)	(0.713)	(1.044)
Observations	47	47	48	48	48	48	48	48
R-squared	0.789	0.595	0.699	0.216	0.366	0.633	0.503	0.326

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Own elaboration based on PIAAC, STEP, WB, EORA, ITU and CISCO data.

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