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ABSTRACT

Workers' Exposure to AI Across Development Stages*

This paper develops a task-adjusted, country-specific measure of workers' exposure to Artificial Intelligence (AI) across 108 countries. Building on Felten et al. (2021), we adapt the Artificial Intelligence Occupational Exposure (AIOE) index to worker-level PIAAC data and extend it globally using comparable surveys and regression-based predictions, covering about 89% of global employment. Accounting for country-specific task structures reveals substantial cross-country heterogeneity: workers in low-income countries exhibit AI exposure levels roughly 0.8 U.S. standard deviations below those in high-income countries, largely due to differences in within-occupation task content. Regression decompositions attribute most cross-country variation to ICT intensity and human capital. High-income countries employ the majority of workers in highly AI-exposed occupations, while low-income countries concentrate in less exposed ones. Using two PIAAC cycles, we document rising AI exposure in high-income countries, driven by shifts in within-occupation tasks rather than employment structure.

JEL Classification: J21, J23, J24

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

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1. Introduction

The rapid progress of large language models (LLMs) and generative AI (GenAI) has drawn considerable public attention, largely due to concerns about potential labour displacement. Yet, empirical evidence on GenAI's labour market effects remains limited, primarily because of scarce systematic data on Artificial Intelligence (AI) investment and application. To address this gap, researchers have turned to measuring workers' exposure to AI, typically combining patent or AI application data with occupational task information (Felten et al., 2021, 2018; Gmyrek et al., 2023; Hampole et al., 2025; Webb, 2020). Most studies focus on the United States, leveraging occupation-level data from the Occupational Information Network (O*NET). However, occupational tasks vary substantially across countries due to differences in technology use, skill supply, and participation in global value chains (Caunedo et al., 2023; Lewandowski et al., 2022). A key question, therefore, is whether AI exposure differs systematically across development levels and what factors drive these differences.

This paper develops a country-specific measure of AI exposure that accounts for variation in occupational tasks across development levels. Building on the task approach to studying the interplay between technology and labour (Acemoglu and Autor, 2011; Autor, 2013), we combine the 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). Together, these sources cover 53 countries at all development levels. We first identify PIAAC questions that best map AI-related capabilities to U.S. occupations. We then apply these mappings to compute AI exposure in countries included in the STEP, PIAAC, and CULS surveys. Finally, we use regression models to examine the determinants of cross-country variation in AI exposure—particularly within similar occupations—and to predict exposure in countries without survey data. In total, we estimate occupational AI exposure for 108 countries, covering about 89% of global employment.

This study makes four main contributions. First, we construct country-specific AI exposure measures that reflect differences in tasks across a wide range of economies. Our regression-based method links O*NET occupational ability requirements to PIAAC-reported job tasks, adapting the AIOE index to U.S. worker-level data and extending it globally. Previous studies measured AI exposure based on occupational tasks (Gmyrek et al., 2025, 2023; Webb, 2020) or abilities (Felten et al., 2021), but their occupation-level estimates did not vary across countries. Gmyrek et al. (2024) adjusted AI exposure using expected computer access in Latin America; however, to our knowledge, this is the first study to use 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 workers' AI exposure across countries and occupations. Exposure increases markedly with development level, both overall and within occupations. Decomposing cross-country variation, we find that task differences explain roughly 78% of the variance, with occupational structure accounting for only 22%. Adjusting for within-occupation task variation amplifies cross-country disparities, especially in low- and middle-income economies and within high-skilled occupations such as managers, professionals, and technicians. Hence, previous studies that did not account for cross-country differences in occupational tasks, e.g. Gmyrek et al. (2023) and Cazzaniga et al. (2024), overestimated AI exposure of workers in low- and middle-income countries. Moreover, using two waves of PIAAC data for high-income countries, we also show that AI exposure has risen since the early 2010s, driven primarily by shifts in within-occupation task structures—underscoring the importance of accounting 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 global economy—measured by forward linkages in global value chains and FDI inflows—is negatively associated. Incorporating workers' cognitive skill measures, such as literacy proficiency, allows us to capture international differences in education quality. Both education and cognitive skills are positively correlated with AI exposure. This has important distributional implications: if AI substitutes for skilled labour, earnings inequality may fall; if it complements skilled labour, inequality may rise. By linking individual human capital directly to workers' AI exposure, we move beyond existing research that typically compares socio-economic groups based on occupational composition alone, overlooking task- and skill-level variation (Cazzaniga et al., 2024; Pizzinelli et al., 2023).

Using our regression results, we decompose cross-country exposure differences and find that ICT intensity—significantly higher in developed economies—accounts for 24–45% of global variance in AI exposure. Occupational composition (19%) and human capital (17%), particularly literacy proficiency (10%), play smaller but meaningful roles. Across multiple ICT infrastructure measures, we confirm that digital technology usage and capability are key drivers of cross-country variation in AI exposure. These findings align with prior work showing that developed countries employ skilled labour more efficiently by adopting technologies such as ICT that complement skilled work (Caselli and Coleman, 2006). Differences in ICT adoption may partly reflect international variation in the supply of skilled labour (Eden and Gaggl, 2020). However, we control for test-based human capital measures that capture schooling quality differences across countries, the key factor behind human capital gaps across the development spectrum (Angrist et al., 2021; Hendricks and Schoellman, 2018; Martellini et al., 2024). Moreover, microdata-based evidence shows that cross-country variation in the skill bias of technology, rather than differences in relative human capital, is the dominant driver of skill premia (Rossi, 2022). This supports our interpretation of ICT as the primary factor explaining international differences in AI exposure, with human capital playing a smaller role.

Fourth, we extend our estimates to 55 additional countries lacking survey data. Estimating occupation-specific models for countries with survey coverage, we predict AI exposure at the 1- and 2-digit levels of the International Standard Classification of Occupations (ISCO-08) for other countries based on their endowments and technology readiness. This expands our coverage to 108 countries, encompassing roughly 89% of global employment. Merging these estimates with occupational composition data, we show that the workers most exposed to AI – the top quartile of the global AI exposure distribution – Is concentrated in high-income countries, while the least exposed workers – the bottom quartile – are predominantly in low- and middle-income economies. These findings challenge the notion of a uniform global AI impact and suggest that high-income countries are likely to experience the most significant short-term effects.

The remainder of the paper proceeds as follows. Section 2 describes the data, measures, and methodology. Section 3 presents results and stylised facts on global disparities in AI exposure. Section 4 concludes.

2. Data and AI exposure measurement

2.1. Data for survey-based measurement of AI exposure

To construct worker-level measures of AI exposure, we combine data from the O*NET occupational abilities database with the U.S. survey 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 abilities, each rated by importance (1-5 scale) and level (1-7 scale). Examples are shown in Appendix Table A1.

PIAAC is a large-scale international survey assessing adults' cognitive skills, job tasks, and skill use. It includes tests of literacy, numeracy, and problem-solving proficiency, and a broad range of work-related questions covering various job tasks and types of computer use.

To extend the analysis beyond the United States, we construct a cross-country, worker-level dataset covering 53 economies at different development levels (Appendix Table A4). The core data come from PIAAC, which collected data in two cycles, each with nationally representative samples of adults aged 16–65. The first cycle comprises three waves (2011–2012, 2014–2015, 2017–2018) in 37 countries. The second cycle (2022–2023) provides data for 18 countries, 15 of which also participated in the first cycle, with occupational information at the 2-digit ISCO-08 level.[1]

We supplement PIAAC with data from the World Bank's *Skills Toward Employment and Productivity* (STEP) survey (World Bank, 2017), covering 12 low- and middle-income countries with urban samples of adults aged 15–64, collected between 2012 and 2014. Because STEP excludes rural areas, we omit ISCO 6 (skilled agricultural workers and farmers) in all countries for consistency. We also include two waves of the *China Urban Labor Survey* (CULS), conducted in 2016 and 2023 by the Chinese Academy of Social Sciences, which contains a task module harmonised with PIAAC and STEP. Following Lewandowski et al. (2022), we reweight data so that national occupational structures align with those from country-specific labour force surveys and ILOSTAT.

2.2. Replicating Felten et al. (2021) AI exposure measures with PIAAC data

The AI exposure index of Felten et al. (2021) maps 10 AI capability dimensions onto 52 O*NET occupational abilities.[2] To extend this framework globally, we first replicate the Felten et al. (2021) index across 2-digit ISCO occupations in the United States using PIAAC survey questions instead of O*NET abilities. Specifically, we identify PIAAC survey questions that best approximate the distribution of each ONET ability across 2-digit ISCO

[1] Belgium, Chile, Czechia, France, Germany, Hungary, Israel, Italy, Japan, Poland, Singapore, Slovakia, South Korea, Spain, and the United States.

[2] Felten et al. (2021) accounted for the following 10 AI dimensions: abstract strategy games, real-time video games, image recognition, visual question answering, generating images, reading comprehension, language modelling, translation, speech recognition, and instrumental track recognition.

occupations in the U.S. We use 18 PIAAC questions: 15 related to routine and non-routine task content (following Lewandowski et al., 2022) and three capturing ICT use and time management (Table 1).[3]

We employ an econometric strategy that links O*NET abilities to PIAAC task measures. Specifically, we regress the occupational relevance of each ability on PIAAC questions using U.S. PIAAC data:

$$Y_{j,o} = \sum_{n}^{N} \beta_{jn} Q_{i,o}^{n} + \epsilon_{i,o} \tag{1}$$

where $Y_{j,o}$ is the product of the O*NET importance and prevalence of ability j in 2-digit ISCO occupation o, and $Q_{i,o}^{n}$ represents responses to PIAAC question n by worker i in occupation o. We treat all question responses as categorical variables in a nonparametric framework, using indicator variables for each response value (e.g., 2–5 on a 1–5 scale, with 1 as the reference category). The dependent variable, $Y_{j,o}$, varies at the occupation level, while explanatory variables vary at the worker level, allowing us later to capture within-occupation heterogeneity and derive individual AI exposure scores.

We narrow the set of O*NET abilities used to compute AI exposure using two criteria. First, we retain abilities with the highest average exposure in Felten et al. (2021). For example, memorisation (AI exposure = 0.84 on 0-1 scale) is kept, while explosive strength (0.26) is excluded. Second, we require that each ability can be reliably approximated by PIAAC task questions in equation (1). To assess this, we compute the correlation between observed $Y_{j,o}$and fitted values. Abilities falling below the median in both AI exposure (0.60) and correlation (0.36) are excluded. The resulting set includes 35 abilities strongly related to AI.[4] Table 2 shows the catalogue of these abilities and their exposures to AI, while Appendix Table A1 provides definitions.

For each of these 35 abilities, estimating equation (1) on U.S. PIAAC data provides coefficients linking PIAAC questions to O*NET abilities at the 2-digit ISCO level. To ensure reliability, we retain questions with the highest correlations to each ability, limit cross-question correlations to below 0.4 to mitigate multicollinearity, and select between three and eight questions per ability. Table 2 presents the ability–question mappings, and Appendix Tables B3–B8 report the estimated coefficients.

We then compute worker-level AI exposure (AIE_{io}) as

$$AIE_{io} = \frac{1}{Y_o} \sum_{j=1}^{35} A_j \Big(\sum_{n}^{N} \hat{\beta}_{jn} Q_i^{n} \Big) \tag{2}$$

where A_j is the AI exposure score of ability j from Felten et al., (2021), and $Y_o$is the number of relevant abilities in occupation o.

[3] Using U.S. survey data on job tasks may introduce two types of bias in measuring AI exposure. On the one hand, since the U.S. is an AI technological leader, some tasks may have already been automated, reducing the frequency of highly exposed tasks and, consequently, workers' exposure. On the other hand, AI adoption may increase the frequency of performing tasks it complements, raising the exposure. However, since the PIAAC data were collected between 2012 and 2023, mostly before the launch of LLM products such as ChatGPT, this bias is most likely negligible since the use of AI in that period was relatively low (Acemoglu et al., 2022).

[4] Replicating Felten et al. (2021) with O*NET and these selected 35 abilities, we find that the results are virtually identical to those based on 52 abilities. The correlation between the two is 0.98 (Appendix Figure B1), validating our approach.

Because the PIAAC, STEP, and CULS surveys provide harmonised worker-level data for 53 countries, applying equation (2) provides country-specific measures of AI exposure that incorporate international variation in job tasks and skill use at work.[5]

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.

[5] We maintain the highest possible level of comparability between PIAAC and STEP / CULS. Appendix Table A3 shows the correspondence between PIAAC and STEP/ CULS questions. The Appendix Tables B9-B14 provide the coefficients estimated for STEP/ CULS data.

Table 2. The mapping between O*NET abilities and PIAAC questions, and the relation between abilities and AI

Ability:	Ability-level exposure (Felten et al. 2021)	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18
Arm-hand steadiness	0.35				X								X				X		
Auditory attention	0.66				X				X	X									
Category flexibility	0.77				X	X	X	X									X		
Deductive reasoning	0.73				X	X	X	X									X		
Dynamic strength	0.27		X		X	X	X	X					X	X			X		
Extent flexibility	0.27	X			X	X	X	X					X	X			X		
Flexibility of closure	0.78					X	X	X				X		X		X	X		
Fluency of ideas	0.61				X	X											X		
Gross-body coordination	0.31		X		X	X	X	X					X	X			X		
Hearing sensitivity	0.62		X		X	X			X	X	X		X		X				
Inductive reasoning	0.71				X	X	X	X						X			X		
Information ordering	0.88					X		X									X		
Mathematical reasoning	0.63	X			X	X	X	X					X			X	X		
Memorization	0.84				X	X											X		
Near vision	0.57					X	X	X						X			X		
Number facility	0.63	X				X	X	X					X	X		X	X		
Oral comprehension	0.67				X	X											X		
Oral expression	0.64				X	X											X		
Originality	0.52				X	X											X		
Perceptual speed	0.76							X			X	X		X	X	X	X		X
Problem sensitivity	0.64					X		X									X		
Response orientation	0.62		X		X	X	X	X					X		X		X		
Selective attention	0.75							X				X		X			X		
Spatial orientation	0.60		X		X	X	X	X						X			X		X
Speech clarity	0.61				X	X											X		

Speech recognition	0.64				X									X			X		
Speed of closure	0.72					X		X									X		
Speed of limb movement	0.79		X		X	X	X	X					X	X			X		
Stamina	0.32		X		X	X	X	X					X	X			X		
Static strength	0.28		X		X	X	X	X					X	X			X		
Timesharing	0.27	X		X				X		X	X	X		X			X		
Visual colour discrimination	0.62		X	X	X				X	X	X		X		X				
Visualization	0.62							X	X		X	X	X		X	X			X
Written comprehension	0.64				X	X											X		
Written expression	0.62	X			X	X	X	X				X		X			X		

Note: Definitions of O*NET abilities are available in Appendix Table A1, full wording of PIAAC questions is available in Appendix Table A3.

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

Our method replicates the distribution of AIOE scores across U.S. occupations with high accuracy. In the United States, the correlation between our PIAAC-based AI exposure estimates and the original Felten et al. (2021) AIOE index is 0.91 across 2-digit ISCO occupations (Figure 1). The correlation with another prominent measure of AI exposure—the occupational exposure to generative pretrained transformers (GPTs) proposed by Eloundou et al. (2024)—is similarly strong at 0.92 (Appendix Figure B2).[6]

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

Notes: Appendix Table A2 presents a detailed list of ISCO08 2-digit occupations.
Source: own elaboration based on Felten et al. (2021) and PIAAC data.

[6] The exposure measures of Felten et al. (2021) and by Eloundou et al. (2024) are highly correlated, with a 0.95 correlation across 2-digit ISCO occupations in the United States. However, we cannot replicate the Eloundou et al. (2024) exposures using PIAAC data in the same way as for Felten et al. (2021). Our approach relies on approximating the distribution of O*NET abilities across 2-digit ISCO-08 occupations with PIAAC survey questions, whereas Eloundou et al. (2024) base their measure directly on job tasks. Because these tasks are largely occupation-specific and provide little variation between occupations, they do not allow for a comparable replication using PIAAC data.

2.3. Econometric methodology

Correlates of AI exposure

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

$$AIE_{ijsc} = \beta_0 + \beta_1 T_{sc} + \beta_2 H_{ijsc} + \tau_o + \beta_3 F_{sc} + \beta_4 D_c + \delta_c^{2022} + \varepsilon_{ijsc} \quad (3)$$

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 $\mathbf{c}$ (including sector fixed effects), D_c comprises development indicators interacted with sector fixed effects, and δ_c^{2022} is a fixed effect for the second PIAAC cycle ((referred to as the *time-trend* in Section 3.2).

We operationalise the key variables as follows (see Table 3 for data sources):

- ICT intensity: share of workers using computers at the country–sector level, including a squared term to capture non-linear effects.
- Human capital: worker-level indicators of educational attainment, test-based literacy proficiency (four levels), gender, and age (in 10-year groups).
- Occupational structure: controlled through 2-digit ISCO fixed effects.
- Firm characteristics: include the share of firms with websites, those using foreign-licensed technology, those holding internationally recognised quality certificates, and measures of forward and backward participation in global value chains (GVCs). All are defined at the country–sector level based on ISIC Rev.4, with 1-digit ISIC sector fixed effects.[7]
- Development indicators: the baseline specification uses demeaned log GDP per capita (PPP) as a proxy for development level, interacted with country–sector fixed effects. Alternative specifications replace GDP with learning-adjusted years of schooling, the Human Capital Index, tertiary enrolment rate, ICT Development Index, Digital Readiness Score, or urbanisation rate.[8]

Because the regressions are cross-sectional, the results describe equilibrium allocations of AI-related tasks rather than causal effects. Nonetheless, ICT intensity and firm characteristics—defined at the aggregate country–sector level—are plausibly exogenous to individual decisions. Human capital, measured at the individual level, primarily reflects pre-market factors such as education and cognitive ability.

[7] Firm-level indicators of digital capability complement our measures of ICT use at work. For example, the correlation between the share of firms with websites and the share of workers using computers at work is only 0.37 across countries and sectors, suggesting they capture distinct aspects of digital capacity.

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

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 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
Share of firms: owning a website; using foreign licensed technology; and having an internationally recognised quality certificate	World Bank Enterprise Survey (WBES)
Human Capital (skill supply and health)	
Human Capital Index (HCI) and its components: learning adjusted years of school (LAYS), harmonised test scores (HLOS), and survival rate from age 15-60 (AMRT)	WDI
Compulsory education duration	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 component) includes: internet usage, mobile cellular subscriptions, and cloud services. Technology infrastructure (DRI component) includes: fixed broadband subscriptions, households' internet access, secure internet services, and mobile broadband subscriptions.

Source: own elaboration.

Decomposition of Cross-Country Variation

To assess the relative contribution of each factor, we use coefficients estimated from equation (3) to predict 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 $\overline{AIE_c}$ is calculated as:

$$\sigma_k = \frac{cov(\beta_k \bar{X}_c^k, \overline{AIE_c})}{var(\overline{AIE_c})} \tag{4}$$

Predicting AI Exposure for Countries Without Task Survey Data

To estimate AI exposure in countries lacking worker-level task data, we predict occupational exposure using OLS regressions estimated at the occupational level for countries with survey data:

$$AIE_{poc} = \beta_{o0} + \beta_{o1} GDP_c + \beta_{o2}\delta_c + \beta_{o3}T_c + \beta_{o4}H_c + \beta_{o5}G_c + \beta_{o6}I_c + \delta_c^{2022} + \gamma_{po} + \varepsilon_{poc} \quad (5)$$

where AIE_{poc} denotes the AI exposure of occupation p (a 2-digit ISCO subcategory within 1-digit occupation o) in country c, γ_{po} are fixed effects for 2-digit occupations within a given 1-digit group, GDP_c is GDP per capita, T_c, H_c, G_c, and I_c are proxies for technology use, human capital, globalisation, and infrastructure, respectively. The term δ_c^{2022} controls for the 2022-2023 survey cycle.

This approach builds on Lewandowski et al. (2023), who estimated country-specific occupational routine task intensity conditional on development level, technology adoption, skill supply, GVC participation, and structural change. We extend their framework by incorporating a broader set of variables to capture technological capacity and human capital more comprehensively (see Table 3).

We estimate prediction models separately for each 1-digit ISCO occupational group, selecting the optimal specification using a stepwise variable selection procedure (Appendix C). Each estimation sample includes 70 country observations, of which 20 are covered in the 2022–2023 surveys and 17 have two survey waves (16 countries from both PIAAC cycles and China from both CULS waves). Control variables correspond to the year of data collection for each country.

We predict occupational AI exposure for 55 additional countries—mainly low- and middle-income economies (Appendix Table A5)—using the most recent available country-level indicators, typically from 2021–2022 (except for GVC data from EORA, 2015, and the ICT Development Index, 2017). Table 4 lists the variables included in the final prediction models, and Appendix Table C1 reports the regression coefficients. The most frequently selected predictors of AI exposure include GDP per capita, the share of the population aged 15–64, urbanisation rate, university enrolment, Digital Readiness Index, internet use, technology infrastructure, and participation in global value chains (Table 4).

Table 4. 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							
Time trend (2022-2023)	X	X	X	X	X	X	X	X
Human Capital Index							X	
Compulsory education		X						
Harmonised test scores			X					
University enrolment		X	X	X				
Survival rate from age 15-60				X	X			X
Share of population aged 15-64	X		X		X		X	X
Population share with electricity		X				X		
Urbanisation					X	X	X	X
ICT development index			X					
Digital Readiness Index				X		X	X	
Internet use	X		X			X		
Technology Infrastructure	X				X			X
Foreign direct investments				X				
GVC participation					X		X	X
ICT imports	X			X				

Notes: School enrolment rate, learning-adjusted years of schooling, technology adoption, and exports were also tested but not selected for any model.
Source: Own elaboration based on PIAAC, STEP, WB, EORA, ITU, and CISCO data.

3. Results

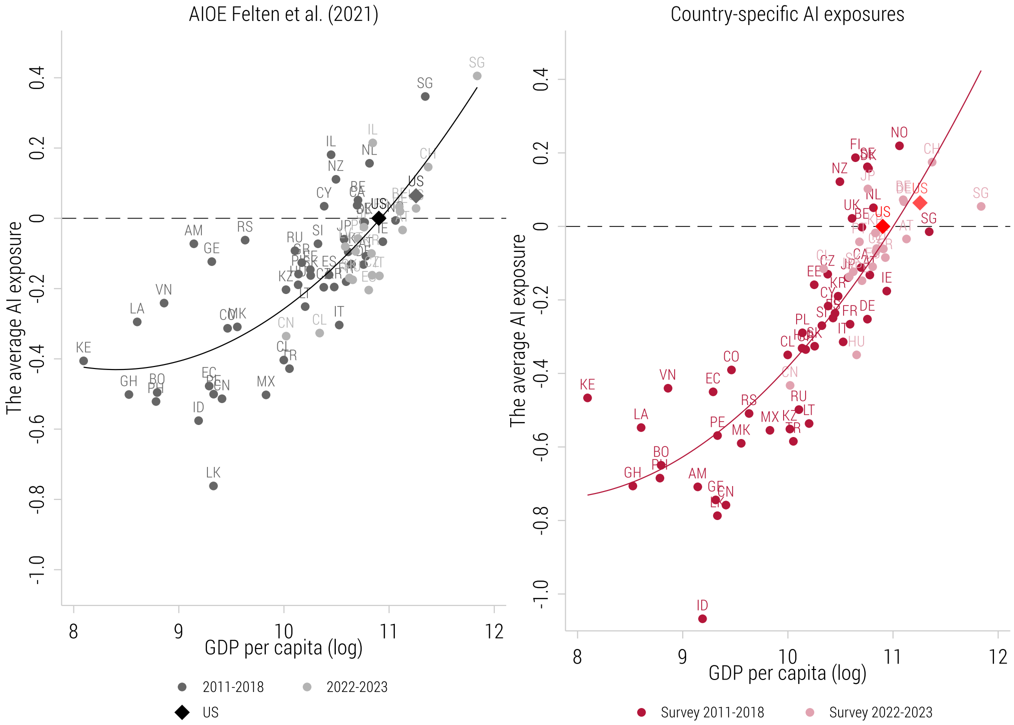
3.1. Descriptive evidence on cross-country differences in AI exposures

Adjusting AI exposure estimates for the cross-country differences in task composition reveals profound disparities across the development spectrum (Figure 2). Comparing survey-based, country-specific exposures (right panel of Figure 2) with the globally applied AIOE index of Felten et al. (2021) (left panel) shows that incorporating country-specific task data amplifies cross-country variation beyond that captured by occupational structure alone. While a higher GDP per capita level is consistently associated with higher average AI exposure, 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 0.8 U.S. standard deviation, indicating that within-occupation task differences between countries account for a substantial share of the exposure gap.[9]

[9] 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 (Appendix Figure B3). This confirms that the observed differences between survey-based and AIOE-based exposures stem from incorporating country-specific task data, not from the substitution of PIAAC questions for O*NET abilities.

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



Note: Survey 2011-2018 includes the first cycle of PIAAC, STEP and 2016 CULS surveys. Survey 2022-2023 includes the second cycle of PIAAC and CULS 2023 surveys. The Spearman correlations between the AI exposure calculated with the most detailed information available in PIAAC/STEP and the exposure calculated only with the set of questions and answers as available in STEP are 69% (country-level average) and 72% (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 assess the relative contributions of occupational structure and task content, we perform a shift-share decomposition of AI exposure for each country. Since zero represents the average U.S. exposure, this is equivalent to decomposing the difference between each country and the United States. The *between-occupation* component captures differences in occupational structures at the 2-digit ISCO level, while the *within-occupation* component quantifies the within-occupation variation in task content.[10]

Task-related factors account for the majority of the cross-country variance in AI exposure (Figure 3). Using a variance–covariance decomposition (Morduch and Sicular, 2002), we find that within-occupation task differences explain 78% of the total variance—more than twice the share explained by occupational structure (31%). The task component is especially large in low- and middle-income countries. The interaction term is generally small and negative (–9%), reflecting that in less developed countries occupations with lower AI exposure than in the U.S.—particularly managerial, professional, and technical—also tend to have lower employment shares.

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

Figure 3. Shift-share decomposition of the differences in AI exposure by country

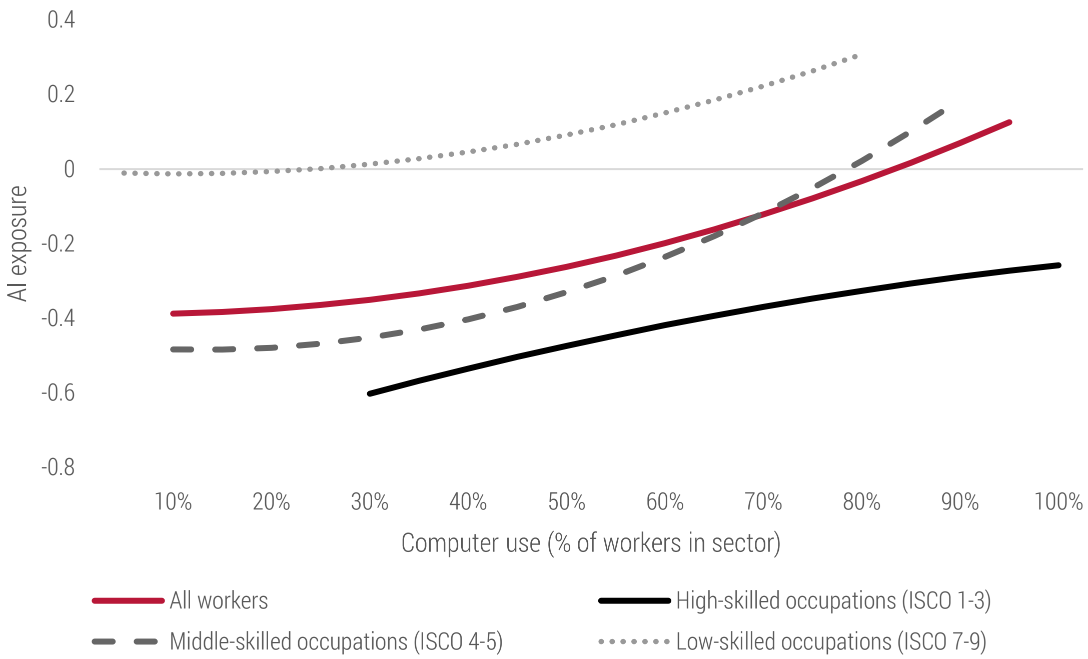
Note: Countries sorted by the average country-level exposure.
Source: Own calculations based on the O*NET, PIAAC, STEP and CULS data.

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

To identify key determinants of AI exposure, we estimate worker-level regressions based on Equation (2). Table 5 reports OLS results for the full sample (columns 1-2) and for a subset of countries with 2-digit ISCO data (columns 3-4). Column 1 excludes occupational fixed effects, while Columns 2-4 progressively control for ISCO-1D and ISCO-2D categories to capture increasingly granular within-occupation variation.

Access to digital technologies is strongly and positively associated with AI exposure, especially in country–sectors where over 60% of workers use computers (Figure 4). A 17 percentage point increase in computer use—comparable to the gap between the U.S. (75%) and China (58%)—raises average AI exposure by 0.10, equivalent to 15% of the U.S.–China difference. This effect is most pronounced among middle-skilled occupations (ISCO 4–5), where a similar increase corresponds to a 0.14 rise in exposure. In contrast, the relationship is weaker among low-skilled workers (ISCO 7–9), particularly in sectors with below-median computer use (40%). Among low-skilled workers a similar increase corresponds to only a 0.09 rise in exposure.

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 4 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 workers in occupations 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.

Human capital is another strong predictor of AI exposure: higher education and literacy proficiency are both associated with significantly greater exposure (Table 5). A worker at the highest literacy level (4–5) has, on average, an AI exposure score 0.13 points higher than a comparable worker at level 2 (medium proficiency). More skilled individuals tend to perform tasks involving analytics and information processing more often, resulting in systematically higher exposure even within narrowly defined occupations. This aligns with prior findings that better-educated workers are more exposed to AI (Cazzaniga et al., 2024; Pizzinelli et al., 2023), but our worker-level approach demonstrates that this relationship also holds within occupations. Since skill-related effects weaken once occupational controls are included (compare Column 1 with Columns 2-4 of Table 5), part of human capital's influence operates through occupational structure. We also find that women and both younger and older workers are less exposed to AI than men and prime-aged workers in similar occupations (Table 5).

Firm and sector characteristics linked to globalisation also shape AI exposure. In countries with average GDP per capita in our sample—such as South Korea or New Zealand—greater forward participation in global value chains (GVCs), measured as domestic value added in other countries' exports (Borin and Mancini, 2019, 2015) is associated with lower AI exposure (Table 5). This effect is strongest in low- and middle-income countries (LMICs) that specialise in upstream GVC activities, such as commodity exports in agriculture and mining, with limited imported inputs (Hanson, 2017; Taglioni and Winkler, 2016).[11] The positive interaction between GVC participation and GDP per capita indicates that the negative effect weakens with higher income and disappears at roughly twice the sample's average GDP per capita (about Germany's 2011-2012 level). These results are consistent with evidence that GVC-intensive work in LMICs is more routine-intensive (Lewandowski et al., 2024). Among other firm characteristics, the prevalence of modern digital tools, such as websites, is also positively associated with AI exposure.

Next, using the estimated coefficients and covariance-based decomposition from Equation (3), we quantify the contribution of each explanatory variable to cross-country variation in AI exposure (Figure 3). The baseline specification controls for GDP per capita; in robustness checks alternative development indicators substitute for it to test if our findings remain valid for various dimensions of developmental gaps. For clarity, we group variables into clusters reflecting fundamental factors, such as human capital or globalisation.

Our models explain 82-86% of the cross-country variance in AI exposure (Table 6). Across all specifications, ICT intensity is the dominant driver, accounting for 24-45% of explained variance, followed by occupational structure (19%) and human capital (17%), with literacy proficiency alone contributing about 10% (detailed results available upon request). Firms' digital adoption and GVC participation account for 2.1-5.6%, while the time-trend component adds around 4.5%. The contributions of human capital and occupational structure remain stable across specifications. The relative importance of ICT intensity declines only when GDP per capita is replaced with aggregate human capital measures, such as the Human Capital Index or learning-adjusted years of schooling—only then does the combined contribution of human capital variables surpass that of ICT.

Overall, these results underscore the central role of ICT infrastructure and digital technology use in shaping AI exposure across development levels. They align with prior evidence that advanced economies employ skilled labour more efficiently by adopting technologies—such as ICT—that complement high-skill work (Caselli and Coleman, 2006), and that cross-country variation in skill premia primarily reflects differences in the skill bias of technology (Rossi, 2022).

[11] Many Sub-Saharan African and Latin American economies exhibit such characteristics.

Table 5. The correlates of individual AI exposures (OLS estimations)

Variable	(1)	(2)	(3)	(4)
ICT intensity	-0.096	-0.084	-0.084	-0.072
	(0.229)	(0.205)	(0.206)	(0.211)
ICT intensity ^ 2	0.881***	0.728***	0.696***	0.644***
	(0.179)	(0.164)	(0.164)	(0.166)
Education: Secondary	0.306***	0.172***	0.167***	0.176***
	(0.014)	(0.012)	(0.012)	(0.012)
Education: Tertiary	0.704***	0.399***	0.401***	0.402***
	(0.020)	(0.016)	(0.017)	(0.016)
Low literacy proficiency (levels 1 or lower)	-0.199***	-0.132***	-0.129***	-0.128***
	(0.012)	(0.009)	(0.010)	(0.009)
Medium literacy proficiency (level 3)	0.166***	0.110***	0.107***	0.097***
	(0.009)	(0.007)	(0.008)	(0.007)
High literacy proficiency (levels 4 and 5)	0.230***	0.155***	0.149***	0.134***
	(0.014)	(0.011)	(0.011)	(0.010)
Gender: Woman	0.106***	-0.028***	-0.020**	-0.130***
	(0.011)	(0.010)	(0.010)	(0.009)
Age: 16-24	-0.209***	-0.208***	-0.208***	-0.202***
	(0.017)	(0.015)	(0.016)	(0.017)
Age: 35-44	-0.015*	-0.020***	-0.022***	-0.014*
	(0.008)	(0.007)	(0.008)	(0.007)
Age: 45-54	-0.048***	-0.041***	-0.040***	-0.044***
	(0.008)	(0.007)	(0.007)	(0.007)
Age: 55-65	-0.111***	-0.114***	-0.112***	-0.116***
	(0.011)	(0.009)	(0.010)	(0.009)
Forward GVC participation (GVCF) exports share	-0.282***	-0.220***	-0.232***	-0.099
	(0.093)	(0.083)	(0.087)	(0.086)
GVCF share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.603***	0.533***	0.527***	0.532***
	(0.153)	(0.142)	(0.142)	(0.137)
Backward GVC participation (GVCB) exports share	-0.111	-0.089*	-0.122**	-0.073
	(0.075)	(0.054)	(0.055)	(0.050)
GVCB share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.031	-0.083	-0.089	-0.093
	(0.087)	(0.067)	(0.067)	(0.065)
Share of firms with a website	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Share of firms using licensed foreign technology	-0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Share of firms with an international quality certificate	0.002***	0.001	0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Ln(GDP per capita) –mean(Ln(GDP per capita))	-0.003	-0.028	-0.022	-0.012
	(0.062)	(0.054)	(0.054)	(0.052)
Time trend (between 2020s and 2010s)	0.026	0.037**	0.041**	0.043**
	(0.020)	(0.018)	(0.018)	(0.017)
Occupation fixed effects	No	ISCO 1D	ISCO 1D	ISCO 2D
Observations	201,568	201,568	171,643	171,643

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, Chile, Japan, Laos, Macedonia, Norway, Philippines, Sri Lanka, and Switzerland are omitted due to unavailability of some control variables. Austria (survey 2011-2018), Canada, Estonia, and Finland are omitted in columns (3) and (4) 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.

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	41.0	44.5	36.9	24.0	25.4	36.0	33.9
Human capital	16.6	17.1	16.9	16.6	16.6	17.1	17.0
Firm characteristics	3.2	2.1	2.7	5.3	5.6	4.9	4.8
Occupational structure	19.5	19.4	19.2	19.2	19.2	19.4	19.2
Development indicators	0.8	-4.4	2.8	15.8	13.5	1.2	3.7
Time trend	3.4	4.4	5.2	4.7	4.9	4.1	4.9
Explained variance	84.5	83.0	83.8	85.7	85.2	82.6	83.5

Note: using variance-covariance decomposition (Morduch and Sicular, 2002). See Table B1 in Appendix B for cross-country variance decomposition from the model without occupational fixed effects (Column 1 of Table 5).
Source: Own estimates based on PIAAC, STEP, WB, EORA, ITU and CISCO data.

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

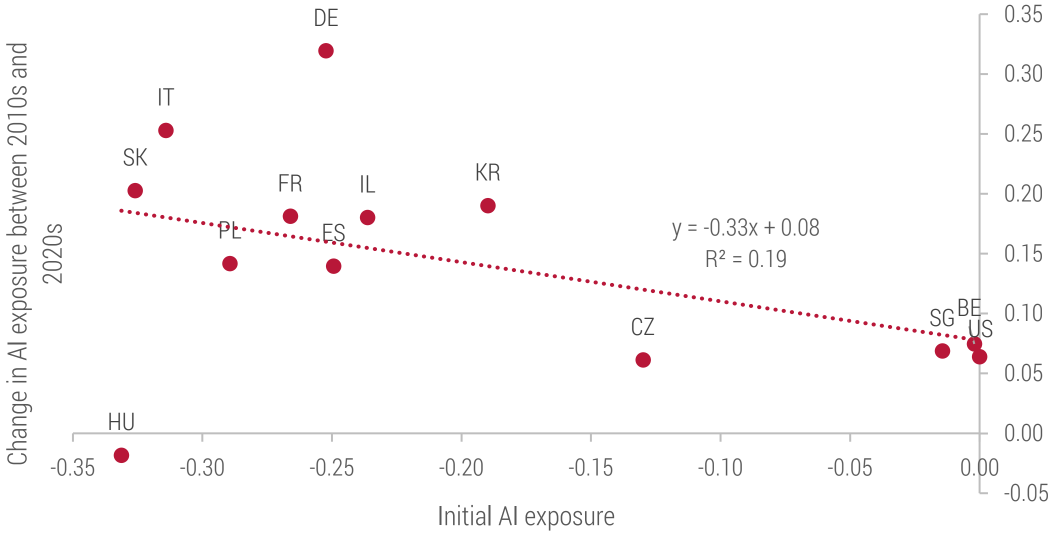
We next examine how AI exposure evolved between the early/mid-2010s and early 2020s using two PIAAC cycles for 13 high-income countries with available 2-digit ISCO08 occupations data and all controls.[12] Compared to our full sample, these economies are characterised by relatively advanced technology adoption and high AI exposure, and they provide the first over-time assessment of changes in job tasks in a large group of countries.

Average AI exposure rose in all countries except Hungary, with the largest increases in lower-tier high-income economies such as Slovakia and Italy. The initial level of exposure is negatively correlated with subsequent change (r = –0.44), suggesting convergence among the countries with available data (Figure 5).

A regression-based decomposition of changes over time, based on Column 4 of Table 5, identifies ICT intensity as the primary driver of rising exposure (Figure 6). The time-trend component—capturing a secular increase in AI exposure across all countries and occupations—also contributes substantially, about half as much as ICT intensity. In contrast, changes in occupational structure play a minor role, with small effects observed only in Italy and Spain. These results indicate that growth in AI exposure largely reflects evolving tasks within occupations rather than shifts in employment composition, highlighting the importance of task-level, survey-based measures.

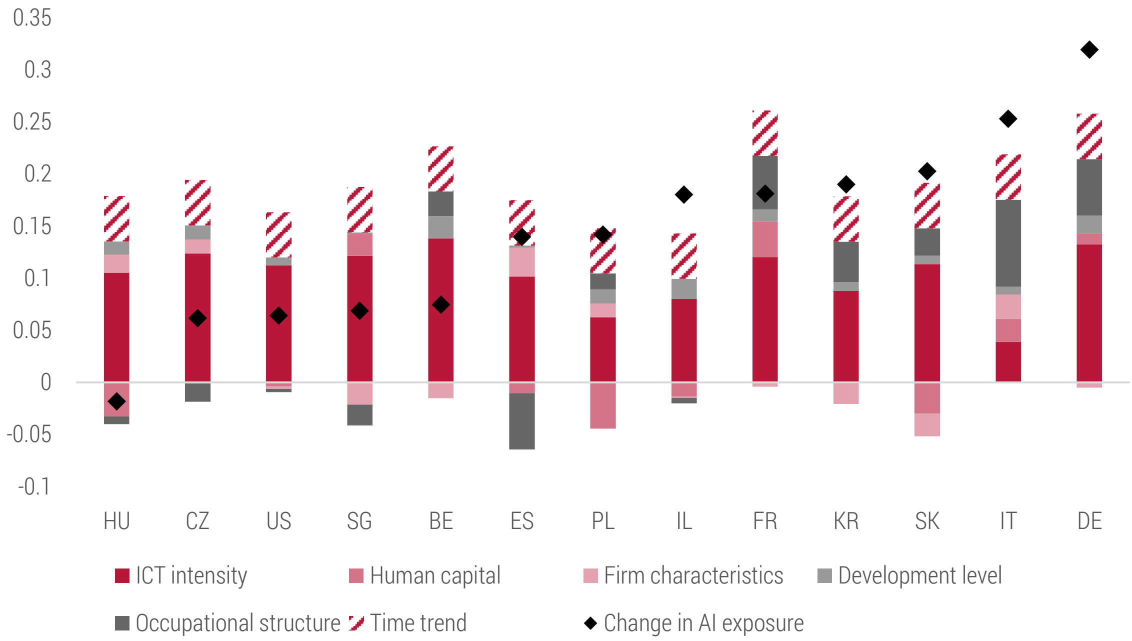
[12] For 10 out of 13 countries studied here, the first cycle PIAAC data were collected in 2011-2012 (BE, CZ, DE, ES, FR, IT, KR, PL, SK, US), for two in 2014-2015 (IL, SG), and for one in 2017-2018 (HU).

Figure 5. Convergence of average AI exposure across developed countries with two cycles of detailed PIAAC data



Note: 13 countries covered by two cycles of PIAAC surveys with 2-digit ISCO occupations available.
Source: Own estimates based on PIAAC data.

Figure 6. Regression-weighted contributions to changes in country AI exposure over time, selected countries with multiple cycles of PIAAC data



Note: Decomposition based on model 4 of Table 5. Computer use measures the share of workers using computers at the country-sector level. Human capital includes worker-level education, literacy proficiency, gender, and age. Firm characteristics include FDIs, backwards and forward GVC participation, share of companies owning a website, using foreign licensed technology, and having an internationally recognised quality certificate, and sector fixed effects. Development level is measured with country GDP per capita interacted with sector fixed effects. Occupational structure is controlled for 2-digit ISCO fixed effects. Time trend is a dummy variable indicating the second wave of the PIAAC study (2022-2023).
Source: Own estimates based on PIAAC, WB, and EORA data.

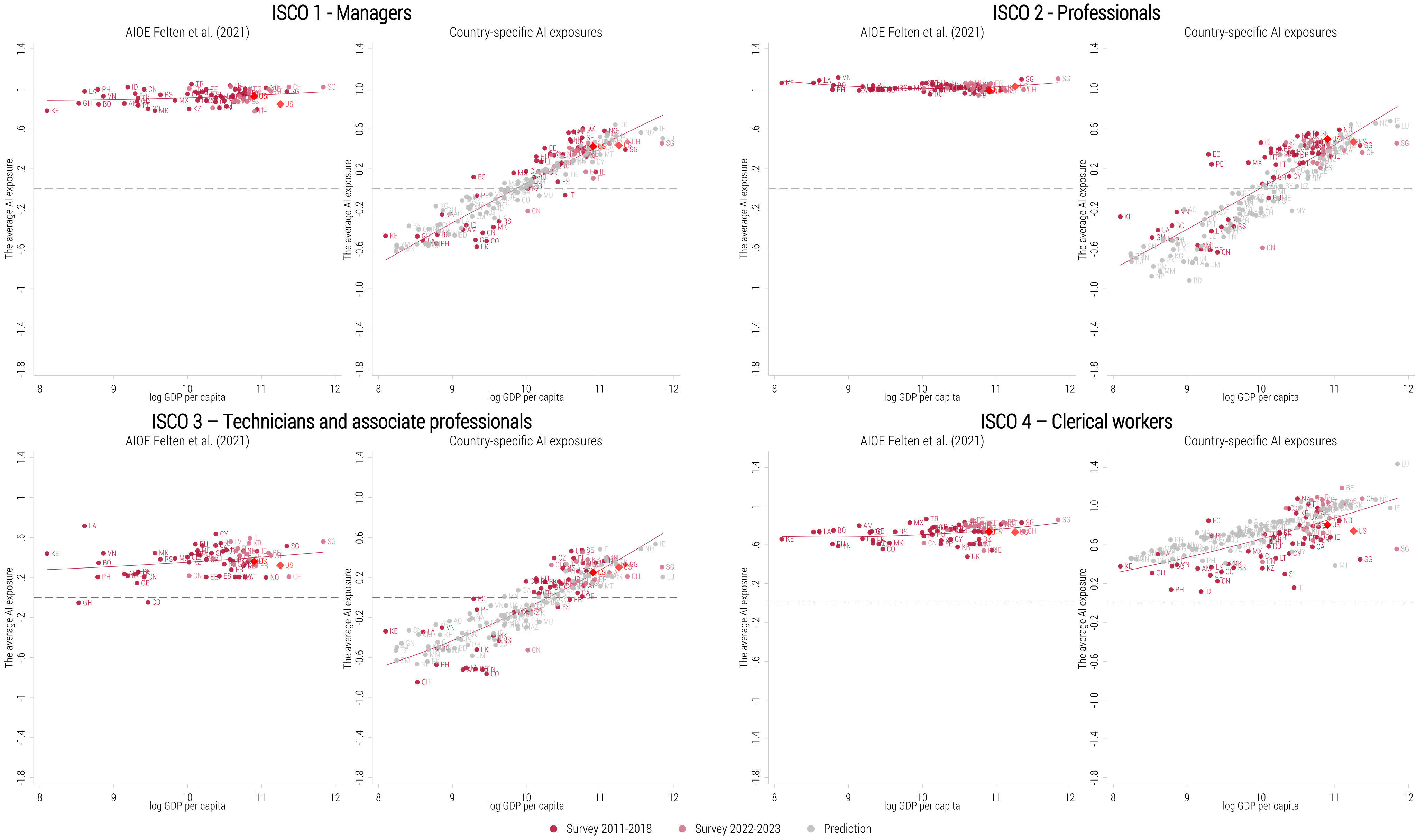
3.4. Global distribution of occupational AI exposures

Finally, we combine survey-based estimates for 53 countries (17 with two waves) with regression-based predictions for 55 additional countries lacking task survey data. Appendix Table A5 lists all countries and their classification into income groups: lower- and upper-tier high-income (HICs), upper-middle-income (UMICs), and low- and lower-middle-income (LMICs). Table 4 in subsection 2.4 provides the list of variables used in the prediction models and Appendix Table B15 shows the regression coefficients. We do not extrapolate beyond the range used to build the prediction models, specifically for countries with a GDP per capita below Kenya ($2687 PPP, on average, between 2011 and 2016), the poorest country in the survey sample. While exposures are estimated at the 2-digit ISCO-08 level, results are aggregated to 1-digit groups for clarity. Predicted exposures refer to the 2020s and incorporate the estimated time-trend, so they are generally slightly higher than the survey-based results for 2011-2018.

For each 1-digit ISCO group, our task-adjusted exposure measure shows substantially greater cross-country variation than the AIOE index (Figure 7). The AIOE variation (left panels) reflects only differences in the composition of 2-digit occupations within each group, whereas our measure (right panels) captures cross-country task differences within occupations.

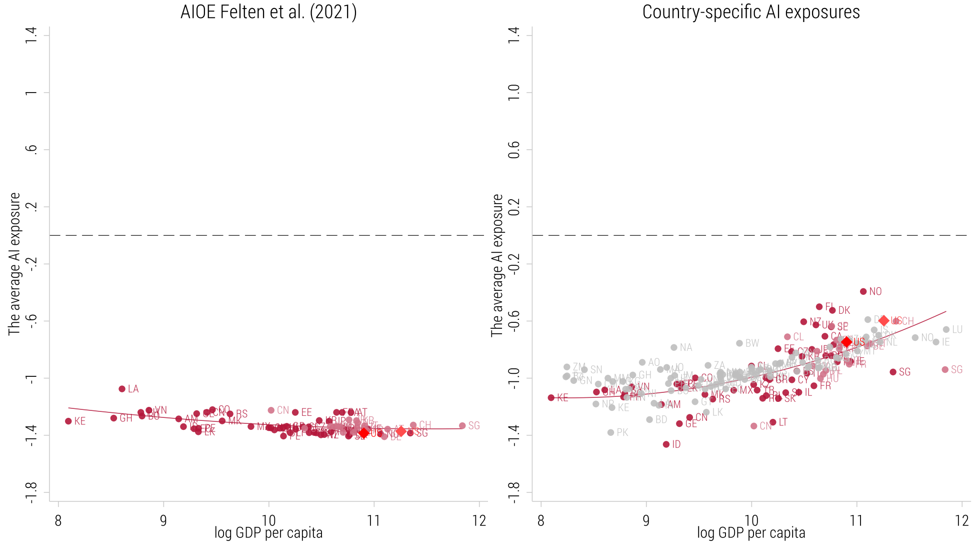
Cross-country variation is greatest among high-skilled occupations (ISCO 1-3), including managers, professionals, and technicians. In these groups, AI exposure rises clearly with GDP per capita, reflecting greater ICT use, technological capabilities and human capital in more developed economies. Among middle-skilled occupations (ISCO 4-5), the relationship is flatter across most of the development spectrum but increases sharply in the most advanced HICs, particularly Scandinavian countries. Clerical support workers (ISCO 4) consistently show the highest exposure across all income groups, suggesting this occupation may face the most widespread global impact from AI adoption. Among low-skilled occupations (ISCO 7-9), exposure also increases with development, though less steeply; elementary occupations (ISCO 9) show no consistent relationship with GDP per capita. Across all low-skilled groups, average exposures remain negative—below the U.S. mean—and well below those for high- and middle-skilled occupations.

Figure 7. 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



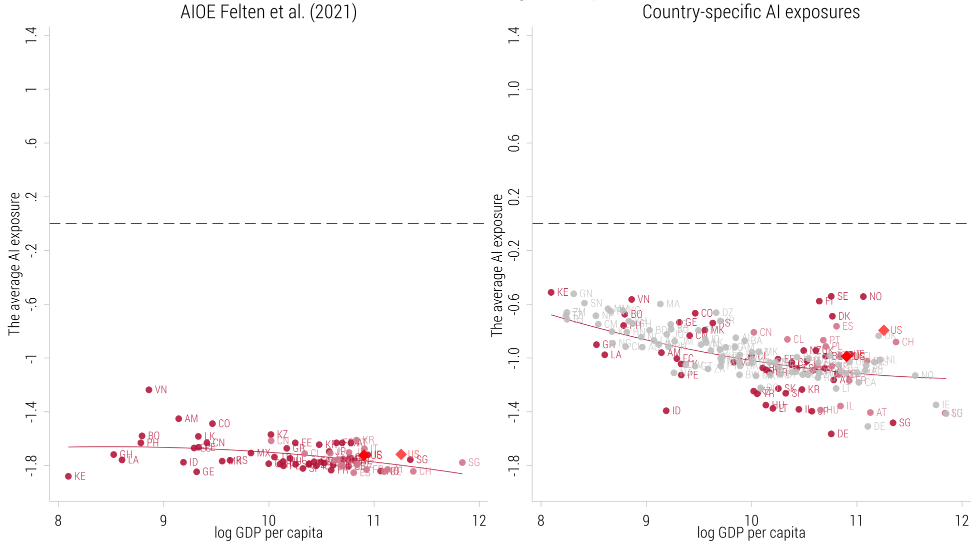
ISCO 5 – Service and sales workers

ISCO 7 – Craft and related trades workers



ISCO 8 – Plant and machine operators, and assemblers

ISCO 9 – Elementary occupations



● Survey 2011-2018 ● Survey 2022-2023 ● Prediction

Note: Survey 2011-2018 includes the first cycle of PIAAC, STEP and 2016 CULS surveys. Survey 2022-2023 includes the second cycle of PIAAC and CULS 2023 surveys. 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.

Combining exposure estimates with the latest occupational structure data from ILOSTAT, we obtain a dataset covering 94 countries (Appendix Table A5), representing roughly 89% of global employment.[13] Weighting exposures by employment shares, we define the least exposed (bottom quartile) and most exposed (top quartile) jobs in the global distribution.

Results reveal substantial polarisation in AI exposure across the development spectrum. High-income countries account for 59.1% of the world's most AI-exposed workers but only 11.9% of the least exposed, despite representing just 25.9% of global employment (Table 7). The pattern is strongest in upper-tier HICs. Upper-middle-income countries—including Brazil, China, and Turkey—host comparable shares of both groups (24.2% of the most exposed and 26.2% of the least exposed), slightly below their 34.0% share of global employment. In contrast, low- and lower-middle-income countries, including India, Indonesia, Philippines, and many African countries, account for 16.7% of the most exposed but as much as 61.8% of the least exposed workers—well above their 40.2% employment share.

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

	Low or lower-middle income	Upper-middle income	Lower-tier high-income	Upper-tier high-income
Most exposed (top 25%)	16.7	24.2	16.9	42.2
Least exposed (bottom 25%)	61.8	26.2	7.1	4.8
Total employment	40.2	34.0	8.4	17.5

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

4. Conclusions

This paper develops a task-adjusted, country-specific measure of workers' exposure to Artificial Intelligence (AI) across a wide range of development contexts. Building on the Artificial Intelligence Occupational Exposure (AIOE) index by Felten et al. (2021), we adapt the measure to U.S. PIAAC data on job tasks to construct a worker-level indicator of AI exposure. We then extend this approach to 53 countries with comparable survey data and generate regression-based predictions for 55 additional countries lacking survey coverage, providing AI exposure estimates for 108 countries. Combined with employment data for 94 countries, our analysis covers roughly 89% of global employment.

A central finding is that accounting for worker-level task variation is crucial to understanding AI exposure. Incorporating country-specific task data reveals pronounced cross-country heterogeneity, especially along the development spectrum. On average, workers in low-income countries exhibit AI exposure levels approximately 0.8 U.S. standard deviations below those in high-income countries. Most of this variation arises from differences in occupational task content rather than occupational structure. The disparity is most evident among high-skilled occupations, where workers perform abstract, non-routine tasks that vary substantially across countries depending on technological capacity, skill supply, and integration into global value chains (Caunedo et al., 2023; Lewandowski

[13] We exclude tax heavens, petrostates, small island countries, and countries without credible employment structure data available from ILOSTAT. Thus, the sample size of countries with occupational AI exposures that can be merged with employment structure data (94) is smaller than the sample size of countries with AI exposures (108).

et al., 2022). By contrast, AI exposure among medium- and low-skilled occupations displays a much flatter relationship with GDP per capita, as task profiles in these groups are more homogeneous internationally.

Using regression-based decompositions, we attribute the majority of cross-country variation in AI exposure to differences in ICT intensity and technological capability, followed by human capital. Consistent with this, AI exposure is strongly and positively associated with education and cognitive skills: more educated and higher-skilled workers systematically perform AI-related tasks more often. At the global level, high-income countries employ the largest share of workers in highly AI-exposed occupations, while low-income countries concentrate a disproportionate share of workers in the least exposed ones.

For the subset of high-income countries observed in two PIAAC cycles, we find a clear increase in AI exposure between the early 2010s and early 2020s, driven primarily by changes in task composition within occupations rather than shifts in employment structure. This underscores the importance of task-level analysis for understanding how modern technologies transform work over time.

These findings carry important policy implications. Advanced economies—where AI-exposed workers are most concentrated—are likely to experience both the benefits and disruptions of AI adoption earlier and more intensely. Yet widespread labour displacement remains unlikely in the short term, as automation of highly exposed tasks is still limited by technical feasibility and cost (Svanberg et al., 2024). Prior research has shown that the development gradient of skill-biased technologies such as ICT contributes to cross-country differences in returns to skills and incomes (Caselli and Coleman, 2006; Rossi, 2022). Our results suggest that similar mechanisms may apply to AI: existing disparities in ICT infrastructure and digital readiness could widen the technological and economic divide between advanced and emerging economies.

A key limitation of our approach is that it focuses on exposure rather than impact. We do not determine whether AI complements or substitutes human labour—a distinction that depends on patterns of actual adoption and task substitution in the workplace. Future work should combine exposure-based measures with empirical evidence on AI implementation to better assess its effects on task composition, skill requirements, labour demand and inequality.

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Appendix A – Methodological details

Table A1. The list of O*NET abilities

Abilities approximated with PIAAC/ STEP:	
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.
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.
dynamic strength	The ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue.
extent flexibility	The ability to bend, stretch, twist, or reach with your body, arms, and/or legs.
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).
gross body coordination	The ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion.
hearing sensitivity	The ability to detect or tell the differences between sounds that vary in pitch and loudness.
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.
near vision	The ability to see details at close range (within a few feet of the observer).
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.
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.
selective attention	The ability to concentrate on a task over a period of time without being distracted.
spatial orientation	The ability to know your location in relation to the environment or to know where other objects are in relation to you.
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.
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.
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).
visual colour discrimination	The ability to match or detect differences between colours, including shades of colour and brightness.
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.

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 A5: Allocation of countries to income groups

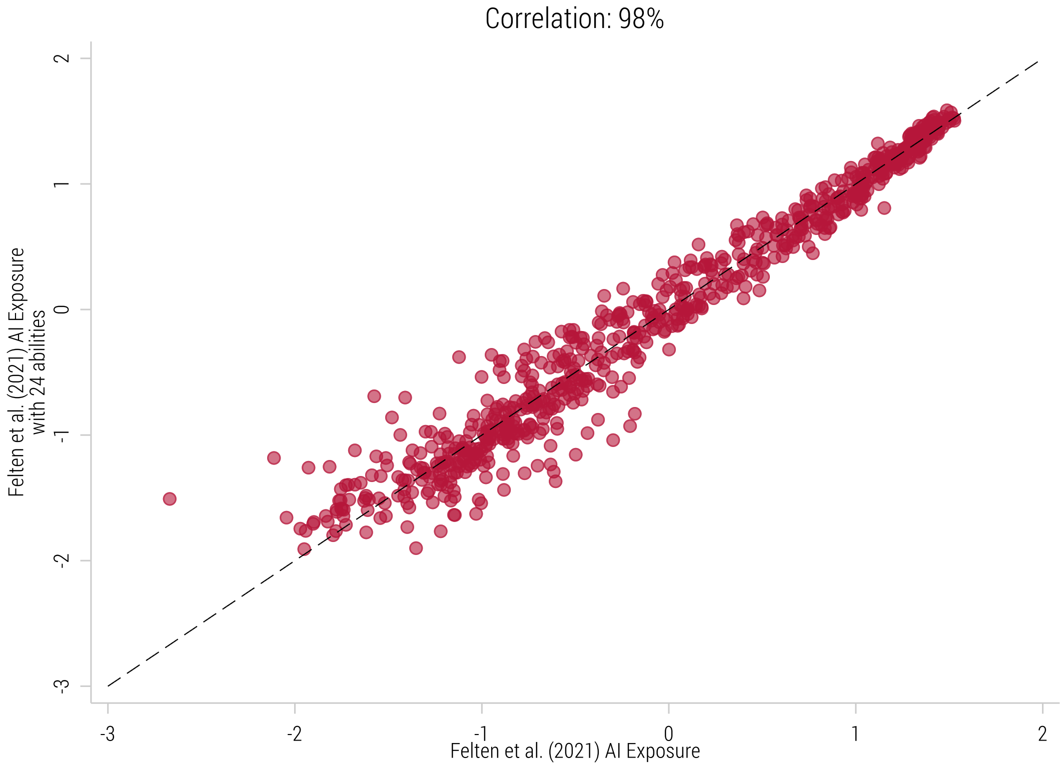
Low- and Lower Middle-Income	Upper Middle-Income	Lower-Tier High-Income	Upper-Tier High-Income
Covered by survey data			
Armenia (STEP)	China (CULS)	Chile (PIAAC 1 & 2)	Austria (PIAAC 1 & 2)
Bolivia (STEP)	Colombia (STEP)	Czechia (PIAAC 1 & 2)	Belgium (PIAAC 1 & 2)
Georgia (STEP)	Ecuador (PIAAC 1)	Cyprus (PIAAC 1)	Canada (PIAAC 1)
Ghana (STEP)	Kazakhstan (PIAAC 1)	Estonia (PIAAC 1)	Denmark (PIAAC 1)
Indonesia (PIAAC 1)	Macedonia (STEP)	Greece (PIAAC 1)	Finland (PIAAC 1)
Kenya (STEP)	Mexico (PIAAC 1)	Hungary (PIAAC 1 & 2)	France (PIAAC 1 & 2)
Laos (STEP)	Peru (PIAAC 1)	Italy (PIAAC 1 & 2)	Germany (PIAAC 1 & 2)
Philippines (STEP)	Serbia (STEP)	Latvia (PIAAC 2)	Ireland (PIAAC 1)
Sri Lanka (STEP)	Turkey (PIAAC 1)	Lithuania (PIAAC 1)	Israel (PIAAC 1 & 2)
Vietnam (STEP)		Poland (PIAAC 1 & 2)	Japan (PIAAC 1 & 2)
		Portugal (PIAAC 2)	Netherlands (PIAAC 1)
		Russia (PIAAC 1)	New Zealand (PIAAC 1)
		Slovakia (PIAAC 1 & 2)	Norway (PIAAC 1)
		Slovenia (PIAAC 1)	Singapore (PIAAC 1 & 2)
		South Korea (PIAAC 1 & 2)	Sweden (PIAAC 1)
		Spain (PIAAC 1 & 2)	Switzerland (PIAAC 2)
			United Kingdom (PIAAC 1)
			United States (PIAAC 1 & 2)
Covered by model-based predictions			
Bangladesh	Albania	Croatia	Australia
Cambodia	Algeria	Uruguay	Iceland
Cameroon	Azerbaijan		Luxembourg
Cote d'Ivoire	Belarus		
Egypt, Arab Rep.	Bosnia and Herzegovina		
El Salvador	Botswana		
Guatemala	Brazil		
Honduras	Bulgaria		
India	Dominican Republic		
Kyrgyz Republic	Iran, Islamic Rep.		
Moldova	Jamaica		
Mongolia	Malaysia		
Morocco	Mauritius		
Myanmar	Montenegro		
Pakistan	Namibia		
Paraguay	Romania		
Ukraine	South Africa		
Zambia	Thailand		

Notes: Surveys time coverage: PIAAC 1 2011-2018, PIAAC 2 2022-2023, STEP 2012-2014, CULS 2016. The allocation of countries to low- and lower middle-, upper middle-, and high-income groups follows the World Bank Analytical Classification. The split between the lower- and upper-tier high income subgroups follows Lewandowski et al. (2022). Countries with AI exposures but without available employment structure data are omitted: Angola, Argentina, Benin, Colombia, Cyprus, Gabon, Guinea, Jordan, Malta, Nicaragua, Nigeria, Senegal, Tunisia, and Uzbekistan.

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

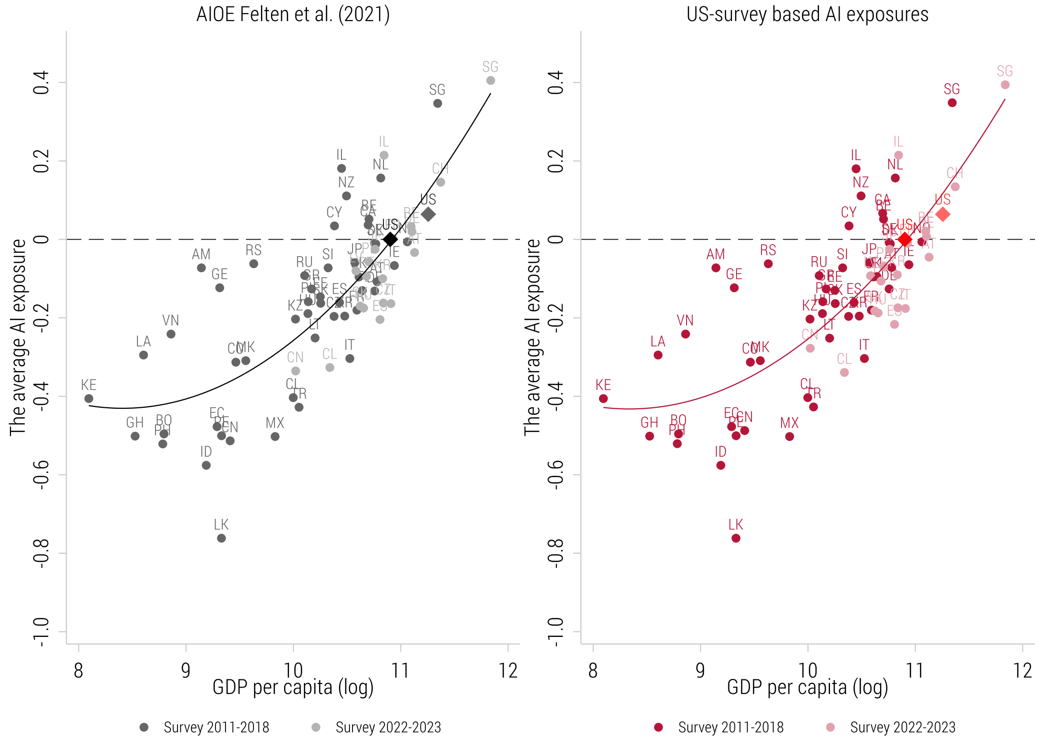


Notes: 6-digit occupations in the SOC10 classification.
Source: own elaboration based on Felten et al. (2021)

Figure B2. The correlation between occupational exposure to GPTs (Eloundou et al., 2024) and task-based exposure to AI calculated with PIAAC survey data for the US

Note: We use GPT exposures based on human ratings (Eloundou et al., 2024).
Source: own elaboration based on Eloundou et al. (2024) and PIAAC data.

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.

Table B1. 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	56.3	66.3	48.4	29.2	35.2	46.3	40.5
Human capital	28.7	29.4	29.0	28.6	28.6	29.0	28.8
Firm characteristics	2.8	0.2	1.8	5.0	4.9	4.9	6.1
Occupational structure	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Development indicators	-7.4	-17.7	-1.1	18.4	11.5	-1.7	3.1
Time trend	2.0	1.4	3.2	3.3	3.2	2.3	3.5
Explained variance	82.4	79.7	81.3	84.5	83.3	80.8	82.0

Note: using variance-covariance decomposition (Morduch and Sicular, 2002).

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

Regression results - PIAAC

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

VARIABLES	(1) Arm-hand steadiness	(2) Auditory attention	(3) Category flexibility	(4) Deductive reasoning	(5) Dynamic strength	(6) Extent flexibility
2.Q16	0.139***		0.042***	0.060***	-0.015***	-0.025***
	(0.014)		(0.008)	(0.010)	(0.005)	(0.009)
3.Q16	0.143***		0.035***	0.054***	-0.021***	-0.039***
	(0.015)		(0.009)	(0.011)	(0.006)	(0.009)
4.Q16	0.117***		0.045***	0.071***	-0.026***	-0.044***
	(0.009)		(0.005)	(0.007)	(0.003)	(0.006)
5.Q16	0.040***		0.046***	0.082***	-0.064***	-0.094***
	(0.005)		(0.003)	(0.004)	(0.002)	(0.003)
2.Q4	0.050***	0.019***	0.021***	0.037***	-0.012***	-0.007*
	(0.006)	(0.002)	(0.004)	(0.005)	(0.002)	(0.004)
3.Q4	0.032***	0.016***	0.017***	0.037***	-0.015***	-0.007
	(0.007)	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)
4.Q4	0.026***	0.012***	0.018***	0.036***	-0.011***	0.001
	(0.009)	(0.004)	(0.005)	(0.006)	(0.003)	(0.005)
5.Q4	0.047***	-0.000	0.023***	0.048***	-0.016***	-0.018***
	(0.008)	(0.003)	(0.005)	(0.006)	(0.003)	(0.005)
2.Q12	0.059***				-0.007**	-0.008*
	(0.008)				(0.003)	(0.005)
3.Q12	0.063***				-0.004	0.001
	(0.008)				(0.003)	(0.005)
4.Q12	0.075***				0.001	0.004
	(0.007)				(0.003)	(0.004)
5.Q12	0.056***				-0.008***	-0.007*
	(0.006)				(0.002)	(0.004)
2.Q8		0.072***				
		(0.003)				
3.Q8		0.080***				
		(0.004)				
4.Q8		0.093***				
		(0.003)				
5.Q8		0.118***				
		(0.002)				
2.Q9		0.056***				
		(0.003)				
3.Q9		0.053***				
		(0.003)				
4.Q9		0.054***				
		(0.002)				
5.Q9		0.055***				
		(0.002)				
2.Q7			0.118***	0.134***	0.033***	0.053***

			(0.004)	(0.005)	(0.003)	(0.004)
3.Q7			0.112***	0.128***	0.028***	0.050***
			(0.004)	(0.005)	(0.003)	(0.004)
4.Q7			0.118***	0.139***	0.028***	0.054***
			(0.004)	(0.005)	(0.003)	(0.004)
5.Q7			0.121***	0.140***	0.031***	0.058***
			(0.004)	(0.006)	(0.003)	(0.005)
2.Q5			0.039***	0.044***	0.004	0.014***
			(0.005)	(0.007)	(0.003)	(0.005)
3.Q5			0.026***	0.031***	0.006	0.015**
			(0.006)	(0.007)	(0.004)	(0.006)
4.Q5			0.028***	0.035***	0.004	0.009*
			(0.005)	(0.006)	(0.003)	(0.005)
5.Q5			0.027***	0.037***	0.003	0.008*
			(0.004)	(0.005)	(0.003)	(0.004)
2.Q6			0.114***	0.126***	0.030***	0.047***
			(0.007)	(0.009)	(0.004)	(0.007)
3.Q6			0.102***	0.120***	0.018***	0.032***
			(0.007)	(0.009)	(0.005)	(0.007)
4.Q6			0.105***	0.122***	0.024***	0.038***
			(0.005)	(0.007)	(0.004)	(0.006)
5.Q6			0.106***	0.124***	0.019***	0.031***
			(0.004)	(0.005)	(0.003)	(0.004)
2.Q13					0.007**	0.018***
					(0.003)	(0.005)
3.Q13					0.002	0.013**
					(0.003)	(0.005)
4.Q13					0.005*	0.017***
					(0.003)	(0.005)
5.Q13					0.015***	0.032***
					(0.002)	(0.004)
2.Q2					0.070***	
					(0.003)	
3.Q2					0.063***	
					(0.003)	
4.Q2					0.060***	
					(0.003)	
5.Q2					0.058***	
					(0.003)	
2.Q1						0.071***
						(0.002)
Observations	4,728	4,724	4,721	4,721	4,712	4,088
R-squared	0.340	0.821	0.906	0.905	0.640	0.628

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	(7) Flexibility of closure	(8) Fluency of ideas	(9) Gross-body coordination	(10) Hearing sensitivity	(11) Inductive reasoning	(12) Information ordering
2.Q16	0.010	0.087***	-0.014**		0.034***	0.073***
	(0.007)	(0.009)	(0.005)		(0.010)	(0.010)
3.Q16	0.008	0.082***	-0.022***		0.036***	0.057***
	(0.007)	(0.010)	(0.006)		(0.010)	(0.010)
4.Q16	0.015***	0.096***	-0.027***		0.046***	0.074***
	(0.004)	(0.006)	(0.004)		(0.006)	(0.006)
5.Q16	0.008***	0.119***	-0.067***		0.055***	0.074***
	(0.003)	(0.003)	(0.002)		(0.004)	(0.004)
2.Q4		0.049***	-0.013***	0.003	0.029***	
		(0.004)	(0.002)	(0.002)	(0.004)	
3.Q4		0.051***	-0.014***	-0.001	0.026***	
		(0.005)	(0.003)	(0.002)	(0.005)	
4.Q4		0.051***	-0.012***	-0.002	0.024***	
		(0.006)	(0.003)	(0.003)	(0.006)	
5.Q4		0.065***	-0.014***	-0.017***	0.039***	
		(0.005)	(0.003)	(0.003)	(0.006)	
2.Q12			-0.007**	-0.001		
			(0.003)	(0.003)		
3.Q12			-0.003	0.001		
			(0.003)	(0.003)		
4.Q12			0.001	0.002		
			(0.003)	(0.002)		
5.Q12			-0.007***	-0.002		
			(0.002)	(0.002)		
2.Q8				0.032***		
				(0.003)		
3.Q8				0.036***		
				(0.003)		
4.Q8				0.047***		
				(0.002)		
5.Q8				0.068***		
				(0.002)		
2.Q9				0.013***		
				(0.003)		
3.Q9				0.011***		
				(0.003)		
4.Q9				0.009***		
				(0.002)		
5.Q9				0.009***		
				(0.003)		
2.Q7	0.068***		0.034***		0.101***	0.173***
	(0.003)		(0.003)		(0.005)	(0.004)
3.Q7	0.064***		0.028***		0.095***	0.170***
	(0.003)		(0.003)		(0.005)	(0.005)
4.Q7	0.071***		0.028***		0.105***	0.176***

	(0.003)		(0.003)		(0.005)	(0.004)
5.Q7	0.074***		0.030***		0.109***	0.180***
	(0.004)		(0.003)		(0.005)	(0.005)
2.Q5	0.022***	0.129***	0.005	0.016***	0.034***	0.107***
	(0.004)	(0.005)	(0.004)	(0.003)	(0.006)	(0.006)
3.Q5	0.014***	0.135***	0.005	0.014***	0.022***	0.101***
	(0.005)	(0.006)	(0.004)	(0.003)	(0.007)	(0.006)
4.Q5	0.017***	0.137***	0.002	0.011***	0.028***	0.103***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.006)	(0.005)
5.Q5	0.015***	0.139***	0.003	0.013***	0.030***	0.105***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)
2.Q6	0.069***		0.033***		0.099***	
	(0.006)		(0.005)		(0.008)	
3.Q6	0.063***		0.021***		0.097***	
	(0.006)		(0.005)		(0.008)	
4.Q6	0.063***		0.025***		0.096***	
	(0.005)		(0.004)		(0.007)	
5.Q6	0.064***		0.019***		0.099***	
	(0.003)		(0.003)		(0.005)	
2.Q13	0.043***		0.007**		0.081***	
	(0.004)		(0.003)		(0.005)	
3.Q13	0.037***		0.002		0.075***	
	(0.004)		(0.003)		(0.006)	
4.Q13	0.037***		0.006**		0.075***	
	(0.004)		(0.003)		(0.005)	
5.Q13	0.043***		0.016***		0.076***	
	(0.003)		(0.002)		(0.004)	
2.Q2			0.074***	0.064***		
			(0.003)	(0.002)		
3.Q2			0.067***	0.061***		
			(0.003)	(0.002)		
4.Q2			0.064***	0.058***		
			(0.003)	(0.002)		
5.Q2			0.061***	0.059***		
			(0.003)	(0.002)		
2.Q11	0.051***					
	(0.003)					
3.Q11	0.046***					
	(0.003)					
4.Q11	0.047***					
	(0.004)					
5.Q11	0.048***					
	(0.004)					
2.Q15	0.003					
	(0.004)					
3.Q15	0.009*					
	(0.005)					
4.Q15	0.007					
	(0.006)					
5.Q15	0.004					

	(0.006)					
2.Q14				-0.006**		
				(0.003)		
3.Q14				-0.003		
				(0.003)		
4.Q14				-0.007***		
				(0.003)		
5.Q14				-0.009***		
				(0.002)		
2.Q10				0.006***		
				(0.002)		
3.Q10				0.003		
				(0.003)		
4.Q10				0.008***		
				(0.003)		
5.Q10				0.006*		
				(0.003)		
Observations	4,722	4,726	4,712	4,714	4,720	4,725
R-squared	0.902	0.846	0.652	0.861	0.908	0.890

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

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

VARIABLES	(13) Mathematical reasoning	(14) Memorization	(15) Near vision	(16) Number facility	(17) Oral comprehension	(18) Oral expression
2.Q16	0.024***	0.064***	0.026**	0.013*	0.174***	0.173***
	(0.007)	(0.006)	(0.010)	(0.007)	(0.016)	(0.016)
3.Q16	0.029***	0.058***	0.023**	0.020***	0.156***	0.156***
	(0.008)	(0.006)	(0.011)	(0.007)	(0.017)	(0.017)
4.Q16	0.034***	0.068***	0.027***	0.021***	0.184***	0.184***
	(0.005)	(0.004)	(0.006)	(0.004)	(0.010)	(0.010)
5.Q16	0.067***	0.072***	0.018***	0.048***	0.183***	0.188***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.006)	(0.006)
2.Q4	0.024***	0.027***			0.063***	0.064***
	(0.003)	(0.003)			(0.007)	(0.007)
3.Q4	0.025***	0.025***			0.058***	0.060***
	(0.004)	(0.003)			(0.009)	(0.008)
4.Q4	0.020***	0.026***			0.055***	0.059***
	(0.004)	(0.004)			(0.010)	(0.010)
5.Q4	0.009**	0.052***			0.111***	0.129***
	(0.004)	(0.003)			(0.009)	(0.009)
2.Q12	0.019***			0.014***		
	(0.004)			(0.004)		
3.Q12	0.016***			0.014***		
	(0.004)			(0.004)		
4.Q12	0.017***			0.015***		
	(0.004)			(0.003)		
5.Q12	0.012***			0.015***		
	(0.003)			(0.003)		
2.Q7	0.044***		0.134***	0.039***		
	(0.003)		(0.005)	(0.003)		
3.Q7	0.047***		0.126***	0.044***		
	(0.004)		(0.005)	(0.003)		
4.Q7	0.054***		0.130***	0.052***		
	(0.003)		(0.005)	(0.003)		
5.Q7	0.053***		0.134***	0.050***		
	(0.004)		(0.005)	(0.003)		
2.Q5	0.014***	0.093***	0.047***	0.017***	0.269***	0.257***
	(0.004)	(0.003)	(0.006)	(0.004)	(0.009)	(0.009)
3.Q5	0.008	0.094***	0.027***	0.009*	0.269***	0.256***
	(0.005)	(0.004)	(0.007)	(0.004)	(0.010)	(0.010)
4.Q5	0.011***	0.093***	0.029***	0.012***	0.266***	0.254***
	(0.004)	(0.003)	(0.006)	(0.004)	(0.008)	(0.008)
5.Q5	0.017***	0.093***	0.027***	0.016***	0.260***	0.250***
	(0.003)	(0.002)	(0.005)	(0.003)	(0.006)	(0.005)
2.Q6	0.035***		0.138***	0.035***		
	(0.006)		(0.008)	(0.005)		
3.Q6	0.039***		0.124***	0.037***		
	(0.006)		(0.008)	(0.005)		
4.Q6	0.036***		0.126***	0.033***		

	(0.005)		(0.007)	(0.004)		
5.Q6	0.043***		0.124***	0.038***		
	(0.004)		(0.005)	(0.003)		
2.Q13			0.099***	0.039***		
			(0.005)	(0.004)		
3.Q13			0.087***	0.039***		
			(0.006)	(0.004)		
4.Q13			0.090***	0.037***		
			(0.005)	(0.003)		
5.Q13			0.099***	0.032***		
			(0.004)	(0.003)		
2.Q1	0.032***			0.032***		
	(0.002)			(0.002)		
2.Q15	0.022***			0.018***		
	(0.004)			(0.004)		
3.Q15	0.038***			0.031***		
	(0.006)			(0.005)		
4.Q15	0.029***			0.023***		
	(0.006)			(0.005)		
5.Q15	0.015**			0.012**		
	(0.006)			(0.005)		
Observations	4,088	4,726	4,723	4,089	4,726	4,726
R-squared	0.878	0.846	0.915	0.897	0.842	0.844

Notes: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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

VARIABLES	(19) Originality	(20) Perceptual speed	(21) Problem sensitivity	(22) Response orientation	(23) Selective attention	(24) Spatial orientation
2.Q16	0.083***	0.020***	0.091***	-0.003	0.024***	-0.004
	(0.009)	(0.007)	(0.012)	(0.006)	(0.008)	(0.004)
3.Q16	0.078***	0.016**	0.074***	-0.013*	0.022***	-0.014***
	(0.009)	(0.007)	(0.013)	(0.007)	(0.008)	(0.005)
4.Q16	0.091***	0.016***	0.097***	-0.016***	0.023***	-0.016***
	(0.006)	(0.005)	(0.008)	(0.004)	(0.005)	(0.003)
5.Q16	0.111***	-0.002	0.087***	-0.055***	0.004	-0.035***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
2.Q4	0.049***			-0.009***		-0.007***
	(0.004)			(0.003)		(0.002)
3.Q4	0.050***			-0.013***		-0.007***
	(0.005)			(0.003)		(0.002)
4.Q4	0.052***			-0.011***		-0.006**
	(0.006)			(0.004)		(0.003)
5.Q4	0.070***			-0.017***		-0.011***
	(0.005)			(0.004)		(0.002)
2.Q12				-0.003		
				(0.004)		
3.Q12				0.000		
				(0.004)		
4.Q12				0.004		
				(0.003)		
5.Q12				0.002		
				(0.003)		
2.Q7		0.098***	0.195***	0.038***	0.123***	0.018***
		(0.003)	(0.005)	(0.003)	(0.004)	(0.002)
3.Q7		0.095***	0.191***	0.037***	0.116***	0.019***
		(0.003)	(0.006)	(0.003)	(0.004)	(0.002)
4.Q7		0.096***	0.200***	0.040***	0.117***	0.021***
		(0.003)	(0.005)	(0.003)	(0.004)	(0.002)
5.Q7		0.100***	0.205***	0.042***	0.119***	0.019***
		(0.004)	(0.006)	(0.004)	(0.004)	(0.002)
2.Q5	0.123***		0.121***	0.002		0.001
	(0.005)		(0.007)	(0.004)		(0.003)
3.Q5	0.129***		0.114***	0.005		0.003
	(0.006)		(0.008)	(0.005)		(0.003)
4.Q5	0.131***		0.118***	0.002		0.002
	(0.004)		(0.006)	(0.004)		(0.003)
5.Q5	0.133***		0.122***	0.004		0.004
	(0.003)		(0.005)	(0.003)		(0.002)
2.Q6				0.023***		0.009***
				(0.005)		(0.004)
3.Q6				0.020***		0.009**
				(0.005)		(0.004)
4.Q6				0.022***		0.010***

		(0.004)		(0.003)
5.Q6		0.019***		0.006***
		(0.003)		(0.002)
2.Q13	0.051***		0.069***	0.007***
	(0.004)		(0.004)	(0.002)
3.Q13	0.045***		0.061***	0.005*
	(0.004)		(0.005)	(0.003)
4.Q13	0.049***		0.063***	0.008***
	(0.004)		(0.004)	(0.002)
5.Q13	0.058***		0.069***	0.013***
	(0.003)		(0.003)	(0.002)
2.Q2		0.065***		0.032***
		(0.003)		(0.002)
3.Q2		0.057***		0.028***
		(0.003)		(0.002)
4.Q2		0.051***		0.026***
		(0.004)		(0.002)
5.Q2		0.048***		0.025***
		(0.004)		(0.002)
2.Q11	0.068***		0.086***	
	(0.003)		(0.004)	
3.Q11	0.062***		0.078***	
	(0.004)		(0.004)	
4.Q11	0.063***		0.079***	
	(0.004)		(0.004)	
5.Q11	0.061***		0.078***	
	(0.004)		(0.004)	
2.Q15	-0.003			
	(0.004)			
3.Q15	0.004			
	(0.006)			
4.Q15	0.003			
	(0.006)			
5.Q15	0.005			
	(0.006)			
2.Q14	0.007*	-0.013***		
	(0.004)	(0.004)		
3.Q14	0.008*	-0.012***		
	(0.004)	(0.004)		
4.Q14	0.012***	-0.013***		
	(0.004)	(0.004)		
5.Q14	0.002	-0.012***		
	(0.003)	(0.003)		
2.Q10	0.004			
	(0.003)			
3.Q10	-0.002			
	(0.004)			
4.Q10	-0.001			
	(0.004)			
5.Q10	-0.001			

		(0.004)				
2.Q18		-0.007				-0.003
		(0.006)				(0.004)
3.Q18		0.006				-0.001
		(0.009)				(0.005)
4.Q18		0.004				-0.000
		(0.008)				(0.005)
5.Q18		0.015***				-0.005
		(0.006)				(0.003)
Observations	4,726	4,725	4,725	4,713	4,727	4,712
R-squared	0.841	0.870	0.878	0.519	0.893	0.426

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

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

VARIABLES	(25) Speech clarity	(26) Speech recognition	(27) Speed of closure	(28) Speed of limb movement	(29) stamina	(30) Static strength
2.Q16	0.138***	0.106***	0.042***	-0.009**	-0.016**	-0.022**
	(0.013)	(0.013)	(0.005)	(0.004)	(0.006)	(0.009)
3.Q16	0.125***	0.125***	0.033***	-0.017***	-0.024***	-0.031***
	(0.014)	(0.014)	(0.006)	(0.004)	(0.006)	(0.009)
4.Q16	0.145***	0.107***	0.045***	-0.020***	-0.029***	-0.041***
	(0.008)	(0.008)	(0.003)	(0.003)	(0.004)	(0.006)
5.Q16	0.148***	0.109***	0.044***	-0.046***	-0.074***	-0.102***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.004)
2.Q4	0.050***	0.046***		-0.010***	-0.014***	-0.020***
	(0.006)	(0.006)		(0.002)	(0.003)	(0.004)
3.Q4	0.048***	0.048***		-0.010***	-0.015***	-0.025***
	(0.007)	(0.007)		(0.002)	(0.003)	(0.005)
4.Q4	0.051***	0.045***		-0.009***	-0.012***	-0.019***
	(0.008)	(0.008)		(0.002)	(0.004)	(0.005)
5.Q4	0.122***	0.071***		-0.012***	-0.015***	-0.025***
	(0.007)	(0.007)		(0.002)	(0.004)	(0.005)
2.Q12				-0.004*	-0.009**	-0.012**
				(0.002)	(0.004)	(0.005)
3.Q12				-0.001	-0.004	-0.007
				(0.002)	(0.003)	(0.005)
4.Q12				0.001	0.001	-0.001
				(0.002)	(0.003)	(0.004)
5.Q12				-0.004**	-0.008***	-0.015***
				(0.002)	(0.003)	(0.004)
2.Q7			0.087***	0.023***	0.038***	0.055***
			(0.002)	(0.002)	(0.003)	(0.004)
3.Q7			0.088***	0.020***	0.031***	0.046***
			(0.003)	(0.002)	(0.003)	(0.005)
4.Q7			0.093***	0.021***	0.030***	0.047***
			(0.002)	(0.002)	(0.003)	(0.004)
5.Q7			0.094***	0.022***	0.033***	0.051***
			(0.003)	(0.002)	(0.003)	(0.005)
2.Q5	0.203***		0.052***	0.001	0.004	0.008
	(0.007)		(0.003)	(0.003)	(0.004)	(0.006)
3.Q5	0.203***		0.050***	0.004	0.005	0.009
	(0.008)		(0.004)	(0.003)	(0.004)	(0.006)
4.Q5	0.201***		0.051***	0.002	0.002	0.005
	(0.006)		(0.003)	(0.002)	(0.004)	(0.005)
5.Q5	0.199***		0.053***	0.002	0.002	0.005
	(0.004)		(0.002)	(0.002)	(0.003)	(0.004)
2.Q6				0.019***	0.037***	0.047***
				(0.003)	(0.005)	(0.007)
3.Q6				0.011***	0.023***	0.029***
				(0.003)	(0.005)	(0.007)
4.Q6				0.014***	0.027***	0.035***

				(0.003)	(0.004)	(0.006)
5.Q6				0.011***	0.021***	0.028***
				(0.002)	(0.003)	(0.005)
2.Q13		0.228***		0.005**	0.008**	0.013***
		(0.006)		(0.002)	(0.003)	(0.005)
3.Q13		0.224***		0.002	0.002	0.005
		(0.007)		(0.002)	(0.004)	(0.005)
4.Q13		0.226***		0.005**	0.006*	0.010**
		(0.006)		(0.002)	(0.003)	(0.005)
5.Q13		0.227***		0.011***	0.017***	0.028***
		(0.005)		(0.002)	(0.003)	(0.004)
2.Q2				0.045***	0.083***	0.109***
				(0.002)	(0.003)	(0.005)
3.Q2				0.040***	0.076***	0.097***
				(0.002)	(0.003)	(0.004)
4.Q2				0.037***	0.071***	0.090***
				(0.002)	(0.003)	(0.005)
5.Q2				0.035***	0.068***	0.087***
				(0.002)	(0.003)	(0.005)
Observations	4,726	4,728	4,725	4,712	4,712	4,712
R-squared	0.839	0.834	0.878	0.557	0.651	0.626

Notes: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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

VARIABLES	(31) Timesharing	(32) Visual colour discrimination	(33) Visualization	(34) Written comprehension	(35) Written expression
2.Q16	0.012**			0.146***	0.038***
	(0.005)			(0.013)	(0.011)
3.Q16	0.011**			0.132***	0.043***
	(0.005)			(0.014)	(0.011)
4.Q16	0.007**			0.163***	0.055***
	(0.003)			(0.008)	(0.007)
5.Q16	-0.003			0.192***	0.099***
	(0.002)			(0.005)	(0.004)
2.Q4		0.001		0.063***	0.035***
		(0.002)		(0.006)	(0.004)
3.Q4		-0.003		0.059***	0.040***
		(0.003)		(0.007)	(0.005)
4.Q4		-0.005*		0.059***	0.047***
		(0.003)		(0.008)	(0.006)
5.Q4		-0.024***		0.107***	0.079***
		(0.003)		(0.008)	(0.006)
2.Q12		-0.002	0.009**		
		(0.003)	(0.004)		
3.Q12		-0.002	0.014***		
		(0.003)	(0.004)		
4.Q12		0.002	0.007*		
		(0.003)	(0.004)		
5.Q12		-0.008***	-0.006*		
		(0.002)	(0.003)		
2.Q8		0.025***	0.051***		
		(0.003)	(0.004)		
3.Q8		0.035***	0.059***		
		(0.004)	(0.005)		
4.Q8		0.044***	0.066***		
		(0.003)	(0.004)		
5.Q8		0.059***	0.091***		
		(0.002)	(0.002)		
2.Q9	0.008***	0.009***			
	(0.003)	(0.003)			
3.Q9	0.008***	0.002			
	(0.003)	(0.003)			
4.Q9	0.008***	0.002			
	(0.002)	(0.003)			
5.Q9	0.009***	0.002			
	(0.003)	(0.003)			
2.Q7	0.033***		0.076***		0.059***
	(0.002)		(0.003)		(0.005)
3.Q7	0.028***		0.076***		0.056***
	(0.002)		(0.004)		(0.005)
4.Q7	0.030***		0.083***		0.065***

	(0.002)		(0.003)		(0.005)
5.Q7	0.029***		0.084***		0.065***
	(0.003)		(0.004)		(0.006)
2.Q5				0.202***	0.016**
				(0.008)	(0.006)
3.Q5				0.205***	0.011
				(0.008)	(0.007)
4.Q5				0.207***	0.020***
				(0.007)	(0.006)
5.Q5				0.206***	0.032***
				(0.005)	(0.005)
2.Q6					0.051***
					(0.008)
3.Q6					0.058***
					(0.009)
4.Q6					0.047***
					(0.007)
5.Q6					0.058***
					(0.005)
2.Q13	0.022***				0.058***
	(0.003)				(0.006)
3.Q13	0.025***				0.062***
	(0.003)				(0.006)
4.Q13	0.025***				0.059***
	(0.003)				(0.006)
5.Q13	0.030***				0.044***
	(0.002)				(0.005)
2.Q2		0.048***			
		(0.003)			
3.Q2		0.048***			
		(0.003)			
4.Q2		0.050***			
		(0.003)			
5.Q2		0.055***			
		(0.003)			
2.Q1	0.035***				0.053***
	(0.001)				(0.003)
2.Q11	0.021***		0.058***		0.045***
	(0.002)		(0.003)		(0.005)
3.Q11	0.017***		0.052***		0.046***
	(0.002)		(0.004)		(0.005)
4.Q11	0.019***		0.053***		0.037***
	(0.002)		(0.004)		(0.005)
5.Q11	0.018***		0.055***		0.034***
	(0.002)		(0.004)		(0.005)
2.Q15			0.013***		
			(0.004)		
3.Q15			0.020***		
			(0.006)		
4.Q15			0.022***		

			(0.006)		
5.Q15			0.020***		
			(0.006)		
2.Q14		-0.008***	0.007*		
		(0.003)	(0.004)		
3.Q14		-0.004	0.009*		
		(0.003)	(0.004)		
4.Q14		-0.010***	0.006		
		(0.003)	(0.004)		
5.Q14		-0.018***	-0.007**		
		(0.002)	(0.003)		
2.Q10	-0.000	0.007**	0.010***		
	(0.002)	(0.003)	(0.003)		
3.Q10	-0.001	0.005*	0.007**		
	(0.003)	(0.003)	(0.004)		
4.Q10	0.006**	0.011***	0.011***		
	(0.003)	(0.003)	(0.003)		
5.Q10	0.003	0.011***	0.010**		
	(0.003)	(0.004)	(0.004)		
2.Q18			0.008		
			(0.006)		
3.Q18			0.029***		
			(0.009)		
4.Q18			0.014*		
			(0.008)		
5.Q18			0.031***		
			(0.006)		
2.Q3	0.085***	0.071***			
	(0.003)	(0.003)			
3.Q3	0.090***	0.077***			
	(0.003)	(0.003)			
4.Q3	0.095***	0.076***			
	(0.003)	(0.003)			
5.Q3	0.102***	0.079***			
	(0.002)	(0.003)			
Observations	4,094	4,272	4,721	4,726	4,089
R-squared	0.948	0.900	0.870	0.855	0.916

Notes: Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Regression results – STEP

Table B9. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(1) Arm-hand steadiness	(2) Auditory attention	(3) Category flexibility	(4) Deductive reasoning	(5) Dynamic strength	(6) Extent flexibility
Physical: 3-4	0.022***	0.007***	-0.008***	-0.014***	0.012***	0.019***
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
5-6	0.033***	0.008***	-0.011***	-0.023***	0.020***	0.030***
	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
7-8	0.057***	0.017***	-0.021***	-0.037***	0.033***	0.053***
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
9-10	0.073***	0.023***	-0.020***	-0.038***	0.041***	0.064***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Use email: No	0.024***	0.009***	-0.023***	-0.042***	0.018***	0.029***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Use computer: No	0.020***	0.006***	0.002	0.002	0.021***	0.033***
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Presenting: No	0.071***	0.113***	0.308***	0.408***	0.016***	0.014***
	(0.006)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
Presenting reversed: No	0.049***	0.105***	0.319***	0.433***	0.006*	-0.002
	(0.006)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
Changing order: Very little	0.005	0.001	-0.004**	-0.006**	0.002	0.004
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
To some extent	0.009***	0.003**	-0.005***	-0.008***	0.002	0.003
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
To high extent	0.008**	0.004**	-0.007***	-0.010***	0.002	0.003
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)
To very high extent	0.014***	0.012***	-0.004*	-0.007*	0.005**	0.005
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
Read news: No	0.010***	0.001	-0.002	-0.007***	0.004**	0.008***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Read professional: No	0.003	0.000	-0.013***	-0.024***	0.004***	0.008***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Use spreadsheets: No	0.026***	0.007***	-0.006***	-0.007***	0.010***	0.016***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Use programming: No	-0.010**	-0.001	-0.010***	-0.008**	0.001	-0.001
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Supervising: No	0.016***	-0.000	-0.009***	-0.022***	0.009***	0.017***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)

Complex problems: Less than once a month	0.002	0.005**	0.008***	0.011***	0.001	0.002
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Less than once a week but at least once a month	0.003	0.008***	0.010***	0.014***	-0.000	0.001
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
A least once a week but not every day	0.007*	0.011***	0.015***	0.022***	0.001	0.003
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Every day	0.013***	0.011***	0.015***	0.020***	0.001	0.005
	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
Fill forms: No	-0.002	-0.006***	-0.002	-0.006***	0.005***	0.008***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Observations	4,712	4,712	4,712	4,712	4,712	4,712
R-squared	0.832	0.930	0.979	0.963	0.788	0.767

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

Table B10. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(7) Flexibility of closure	(8) Fluency of ideas	(9) Gross-body coordination	(10) Hearing sensitivity	(11) Inductive reasoning	(12) Information ordering
Physical: 3-4	-0.003	-0.016***	0.012***	0.006***	-0.012***	-0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
5-6	-0.004	-0.026***	0.021***	0.007**	-0.020***	-0.012***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.003)
7-8	-0.007***	-0.039***	0.036***	0.017***	-0.032***	-0.020***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
9-10	-0.005***	-0.041***	0.043***	0.024***	-0.032***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Use email: No	-0.020***	-0.030***	0.020***	0.007***	-0.045***	-0.024***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Use computer: No	0.007***	-0.006**	0.020***	0.007***	0.002	0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Presenting: No	0.239***	0.301***	0.016***	0.096***	0.374***	0.353***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.006)	(0.003)
Presenting reversed: No	0.243***	0.328***	0.006*	0.089***	0.399***	0.363***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)	(0.003)
Changing order: Very little	-0.002	-0.009***	0.003	0.001	-0.004	-0.004**

	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
To some extent	-0.003	-0.010***	0.003	0.002	-0.005*	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
To high extent	-0.004*	-0.012***	0.002	0.003	-0.006*	-0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
To very high extent	0.002	-0.011***	0.004*	0.009***	-0.003	-0.004*
	(0.003)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)
Read news: No	-0.001	-0.007***	0.003*	0.001	-0.007**	-0.003
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Read professional: No	-0.012***	-0.021***	0.005***	-0.002	-0.026***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Use spreadsheets: No	-0.000	-0.007***	0.013***	0.008***	-0.001	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Use programming: No	-0.012***	-0.010***	0.004*	-0.004**	-0.006*	-0.016***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Supervising: No	-0.008***	-0.021***	0.008***	-0.000	-0.018***	-0.013***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Complex problems: Less than once a month	0.009***	0.008***	0.000	0.005***	0.011***	0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Less than once a week but at least once a month	0.013***	0.010***	-0.001	0.008***	0.013***	0.012***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
A least once a week but not every day	0.018***	0.017***	-0.001	0.011***	0.021***	0.017***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Every day	0.019***	0.014***	-0.000	0.012***	0.021***	0.018***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)
Fill forms: No	-0.006***	0.002	0.004***	-0.005***	-0.008***	-0.004**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Observations	4,712	4,712	4,712	4,712	4,712	4,712
R-squared	0.959	0.942	0.799	0.912	0.956	0.981

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

Table B11. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(13) Mathematical reasoning	(14) Memorization	(15) Near vision	(16) Number facility	(17) Oral comprehension	(18) Oral expression
Physical: 3-4	-0.012***	-0.007***	-0.007***	-0.011***	-0.014***	-0.017***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
5-6	-0.018***	-0.013***	-0.009***	-0.017***	-0.024***	-0.028***
	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)
7-8	-0.036***	-0.017***	-0.018***	-0.031***	-0.038***	-0.043***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
9-10	-0.039***	-0.017***	-0.018***	-0.033***	-0.041***	-0.047***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Use email: No	-0.026***	-0.016***	-0.024***	-0.019***	-0.038***	-0.041***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Use computer: No	-0.006**	-0.007***	0.002	-0.007***	-0.013***	-0.017***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Presenting: No	0.254***	0.176***	0.379***	0.241***	0.469***	0.462***
	(0.005)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Presenting reversed: No	0.266***	0.190***	0.383***	0.249***	0.493***	0.494***
	(0.004)	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
Changing order: Very little	-0.007***	-0.001	-0.000	-0.006***	-0.003	-0.003
	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
To some extent	-0.009***	0.000	-0.001	-0.008***	-0.001	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
To high extent	-0.010***	-0.000	-0.002	-0.008***	-0.002	-0.000
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
To very high extent	-0.008**	0.002	-0.001	-0.007**	-0.002	0.000
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
Read news: No	-0.002	-0.004***	0.000	-0.002	-0.010***	-0.012***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Read professional: No	-0.009***	-0.010***	-0.011***	-0.006***	-0.021***	-0.023***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Use spreadsheets: No	-0.023***	-0.001	-0.005***	-0.019***	-0.000	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Use programming: No	-0.018***	0.001	-0.007***	-0.012***	0.006**	0.013***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Supervising: No	-0.021***	-0.008***	-0.002	-0.020***	-0.015***	-0.016***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Complex problems: Less	0.007**	0.005***	0.008***	0.005**	0.009***	0.010***

than once a month						
	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Less than once a week but at least once a month	0.013***	0.006***	0.012***	0.011***	0.009***	0.008**
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
A least once a week but not every day	0.020***	0.009***	0.015***	0.016***	0.011***	0.010***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Every day	0.016***	0.007***	0.016***	0.012***	0.009**	0.005
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
Fill forms: No	-0.005***	-0.003***	-0.007***	-0.005***	-0.010***	-0.011***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	4,712	4,712	4,712	4,712	4,712	4,712
R-squared	0.906	0.965	0.989	0.930	0.979	0.971

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

Table B12. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(19) Originality	(20) Perceptual speed	(21) Problem sensitivity	(22) Response orientation	(23) Selective attention	(24) Spatial orientation
Physical: 3-4	-0.015***	0.001	-0.007*	0.011***	-0.000	0.006***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)
5-6	-0.023***	0.001	-0.014***	0.016***	-0.002	0.009***
	(0.004)	(0.003)	(0.005)	(0.004)	(0.002)	(0.003)
7-8	-0.035***	0.001	-0.020***	0.032***	-0.002	0.017***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(0.002)
9-10	-0.036***	0.005***	-0.016***	0.040***	-0.000	0.020***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Use email: No	-0.028***	-0.010***	-0.037***	0.017***	-0.009***	0.011***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)
Use computer: No	-0.007**	0.009***	0.003	0.021***	0.001	0.015***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)
Presenting: No	0.285***	0.207***	0.399***	0.015***	0.250***	0.010***
	(0.005)	(0.003)	(0.006)	(0.005)	(0.002)	(0.003)
Presenting reversed: No	0.314***	0.202***	0.415***	0.003	0.252***	0.004
	(0.005)	(0.003)	(0.005)	(0.004)	(0.002)	(0.003)
Changing order: Very little	-0.009***	-0.000	-0.005	0.003	-0.000	0.001
	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
To some extent	-0.009***	-0.000	-0.006**	0.004	0.002*	0.001

	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
To high extent	-0.012***	-0.001	-0.007*	0.005*	0.002	0.003
	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(0.002)
To very high extent	-0.010***	0.006**	-0.003	0.015***	0.007***	0.009***
	(0.004)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)
Read news: No	-0.007***	0.001	-0.007***	0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Read professional: No	-0.021***	-0.006***	-0.024***	0.001	-0.006***	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Use spreadsheets: No	-0.005**	-0.001	0.005*	0.011***	0.002*	0.003*
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Use programming: No	-0.010***	-0.011***	-0.006*	0.000	-0.005***	-0.000
	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)
Supervising: No	-0.021***	-0.004***	-0.024***	0.007***	-0.004***	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Complex problems: Less than once a month	0.008**	0.007***	0.010***	0.004	0.005***	0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)
Less than once a week but at least once a month	0.008***	0.012***	0.012***	0.006**	0.008***	0.004**
	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(0.002)
A least once a week but not every day	0.016***	0.015***	0.019***	0.008***	0.011***	0.006***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)
Every day	0.013***	0.017***	0.020***	0.007**	0.011***	0.003
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)
Fill forms: No	0.004*	-0.008***	-0.010***	-0.004**	-0.006***	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	4,712	4,712	4,712	4,712	4,712	4,712
R-squared	0.934	0.956	0.963	0.643	0.987	0.523

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

Table B13. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(25) Speech clarity	(26) Speech recognition	(27) Speed of closure	(28) Speed of limb movement	(29) Stamina	(30) Static strength
Physical: 3-4	-0.013***	-0.011***	-0.005***	0.008***	0.015***	0.019***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
5-6	-0.025***	-0.020***	-0.009***	0.013***	0.024***	0.030***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)
7-8	-0.036***	-0.031***	-0.012***	0.022***	0.040***	0.053***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
9-10	-0.038***	-0.034***	-0.012***	0.028***	0.048***	0.066***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Use email: No	-0.030***	-0.022***	-0.017***	0.014***	0.022***	0.030***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Use computer: No	-0.016***	-0.017***	0.001	0.017***	0.021***	0.030***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Presenting: No	0.359***	0.367***	0.187***	0.004	0.017***	0.018***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.006)
Presenting reversed: No	0.389***	0.379***	0.192***	-0.004	0.007*	0.002
	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Changing order: Very little	-0.003	-0.003	-0.002	0.002	0.003	0.003
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)
To some extent	0.002	-0.002	-0.002	0.002	0.003*	0.004
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
To high extent	0.002	-0.001	-0.002	0.003	0.003	0.005
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
To very high extent	0.004	-0.002	0.001	0.007***	0.005*	0.013***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Read news: No	-0.010***	-0.007***	-0.002*	0.002	0.004**	0.005*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Read professional: No	-0.018***	-0.010***	-0.011***	0.003**	0.006***	0.006**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Use spreadsheets: No	-0.001	-0.002	-0.002	0.007***	0.014***	0.019***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Use programming: No	0.021***	0.014***	-0.006***	0.001	0.004*	0.004
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Supervising: No	-0.014***	-0.016***	-0.011***	0.007***	0.009***	0.016***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Complex problems: Less	0.008**	0.003	0.005***	0.002	-0.000	0.004

than once a month	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Less than once a week but at least once a month	0.004	0.002	0.009***	0.001	-0.002	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
A least once a week but not every day	0.005	0.002	0.012***	0.003	-0.002	0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Every day	-0.000	0.000	0.012***	0.002	-0.001	0.004
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Fill forms: No	-0.007***	-0.008***	-0.005***	0.002**	0.006***	0.006**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	4,712	4,712	4,712	4,712	4,712	4,712
R-squared	0.967	0.982	0.959	0.701	0.801	0.774

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

Table B14. Estimation of the STEP question weights for O*NET abilities

VARIABLES	(31) Timesharing	(32) Visual colour discrimination	(33) Visualization	(34) Written comprehension	(35) Written expression
Physical: 3-4	0.002*	0.008***	0.003	-0.019***	-0.020***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
5-6	0.000	0.013***	0.006	-0.031***	-0.035***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
7-8	0.003**	0.023***	0.010***	-0.054***	-0.058***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
9-10	0.006***	0.028***	0.018***	-0.058***	-0.062***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Use email: No	-0.001	0.002	-0.003	-0.054***	-0.055***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Use computer: No	-0.003***	0.011***	0.017***	-0.009**	-0.011**
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Presenting: No	0.187***	0.136***	0.194***	0.437***	0.399***
	(0.002)	(0.003)	(0.005)	(0.006)	(0.007)
Presenting reversed: No	0.189***	0.130***	0.194***	0.469***	0.436***
	(0.002)	(0.003)	(0.004)	(0.006)	(0.006)
Changing order: Very little	-0.001	0.000	-0.005*	-0.005	-0.007*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
To some extent	0.001	0.000	-0.006**	-0.005	-0.006*

	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
To high extent	0.002	-0.001	-0.007**	-0.007*	-0.008*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
To very high extent	0.004***	0.003	0.000	-0.005	-0.006
	(0.001)	(0.003)	(0.003)	(0.005)	(0.005)
Read news: No	-0.003***	0.005***	0.003	-0.009***	-0.012***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Read professional: No	-0.005***	-0.005***	-0.009***	-0.027***	-0.029***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Use spreadsheets: No	0.006***	0.009***	0.003	-0.013***	-0.013***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Use programming: No	0.005***	-0.011***	-0.022***	0.001	0.006
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Supervising: No	-0.009***	-0.001	-0.003	-0.019***	-0.024***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Complex problems: Less than once a month	0.001	0.005**	0.010***	0.014***	0.014***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Less than once a week but at least once a month	0.003**	0.007***	0.016***	0.016***	0.014***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
A least once a week but not every day	0.003***	0.012***	0.025***	0.020***	0.019***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Every day	0.002	0.013***	0.026***	0.017***	0.015***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Fill forms: No	-0.006***	-0.001	0.001	-0.011***	-0.010***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Observations	4,712	4,712	4,712	4,712	4,712
R-squared	0.983	0.930	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

Appendix C – Out-of-sample predictions of country-specific occupational AI exposures

We estimate prediction models separately for 1-digit ISCO occupational groups, identifying the optimal specification with a stepwise variable selection procedure

First, we implement 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 and δ_c as baseline controls.

Second, we evaluate model performance using leave-one-out cross-validation (LOOCV). We estimate each model using all but one country and predict the excluded observation, repeating the process across the sample. For each 1-digit occupation, we retain the highest predictive accuracy model from both selection strategies. We use a maximum of seven explanatory variables to mitigate overfitting. We apply a variance-covariance decomposition of prediction and drop variables contributing the least to the explained variance. We also prioritise specific (e.g., learning-adjusted years of schooling) over composite indicators (e.g., the HCI), aiming for greater data-driven variability and interpretability.

Third, 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 occupations to allow predictions at a more granular occupational level.

Table C1. 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	0.648	0.428***	0.319***	0.079	-0.130	0.012	-0.036	-0.351***
	(0.600)	(0.053)	(0.087)	(0.085)	(0.095)	(0.073)	(0.069)	(0.101)
log (GDP pc)^2	-0.021							
	(0.029)							
Time trend (2022-2023)	-0.112*	-0.190***	-0.194**	0.180***	0.196**	-0.016	0.068	0.102
	(0.056)	(0.059)	(0.079)	(0.066)	(0.075)	(0.056)	(0.053)	(0.081)
Human Capital Index							0.259	
							(0.438)	
Compulsory education		0.050***						
		(0.012)						
Harmonised test scores			0.002**					
			(0.001)					
University enrolment		0.003**	0.003*	0.002				
		(0.002)	(0.002)	(0.002)				
Survival rate from age 15-60				0.590	1.712**			1.371*
				(0.617)	(0.736)			(0.787)
Share of population aged 15-64	-0.021***		-0.027***		-0.015**		-0.010*	-0.005
	(0.006)		(0.006)		(0.008)		(0.005)	(0.008)
Population share with electricity		-0.010***				-0.008***		
		(0.004)				(0.003)		
Urbanisation					-0.003	0.001	-0.001	0.000
					(0.002)	(0.002)	(0.002)	(0.002)
ICT development index			-0.113**					
			(0.054)					
Digital Readiness Index				0.053		0.072	0.169***	
				(0.070)		(0.057)	(0.058)	
Internet use	0.007***		0.007*			0.006***		
	(0.002)		(0.003)			(0.002)		
Technology Infrastructure	0.051				0.175***			0.150**
	(0.044)				(0.061)			(0.065)
Foreign direct investments				-0.002				
				(0.001)				
Participation in GVC, forward (EORA), 2011-2015					0.808			0.716
					(0.517)			(0.553)
Participation in GVC, backward (EORA), 2011-2015							-0.317**	
							(0.146)	
ICT imports	0.003			-0.012***				
	(0.004)			(0.004)				
Constant	-3.358	-3.889***	-2.176***	-0.748	0.336	-0.807	-0.260	1.379
	(2.938)	(0.461)	(0.674)	(0.761)	(0.833)	(0.603)	(0.634)	(0.890)
Observations	70	70	70	70	70	70	70	70
R-squared	0.844	0.756	0.780	0.567	0.388	0.572	0.382	0.248

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.