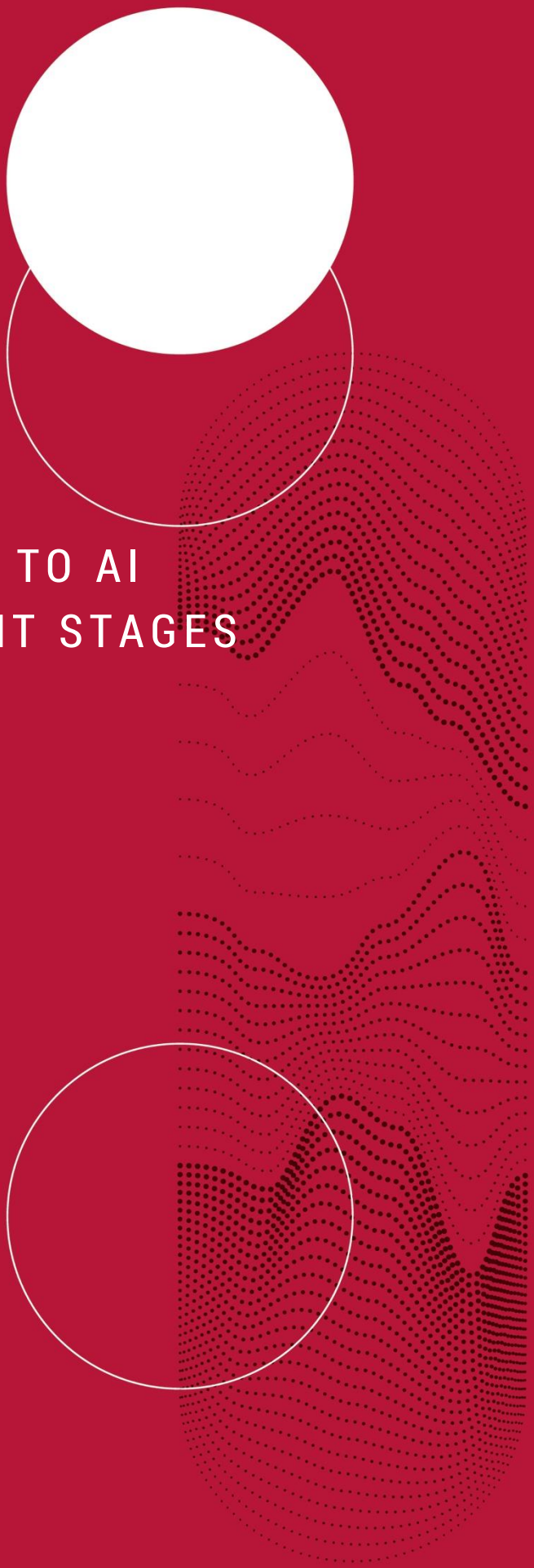
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WORKERS' EXPOSURE TO AI ACROSS DEVELOPMENT STAGES•

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Abstract

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: in most occupations, workers in less-developed countries exhibit lower AI exposure than their peers in high-income countries. Cross-country differences in within-occupation task content contribute as much as differences in occupational structures to the differences in AI exposure across the development spectrum. High-income countries employ the majority of workers in highly AI-exposed occupations, while low-income countries concentrate in less exposed ones. Regression decompositions attribute most cross-country variation to ICT intensity and human capital.

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

JEL: J21, J23, J24

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1. Introduction

The rapid progress of large language models (LLMs) and generative AI (GenAI) has 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 a scarcity of wide-scale 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., 2025; Hampole et al., 2025; Septiandri et al., 2024; Webb, 2020). Most studies focus on the United States, leveraging occupation-level data from the Occupational Information Network (O*NET). However, occupational tasks vary across the development spectrum 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 between less and more developed countries and what factors drive these differences.

This paper develops a country-specific measure of AI exposure that accounts for variation in job 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 54 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. Next, we use regression models to examine the drivers of cross-country variation in AI exposure—particularly within occupations—and to predict exposure in 54 countries without survey data, conditional on their endowments and technology readiness. In total, we estimate occupational AI exposure at the 1- and 2-digit levels of the International Standard Classification of Occupations (ISCO-08) for 108 countries, covering almost 90% of global employment. This allows establishing stylised facts on global differences in task-adjusted AI exposure.

This study makes three main contributions. First, we construct country-specific AI exposure measures that reflect differences in tasks across a wide range of countries. Our regression-based method links O*NET occupational ability requirements to PIAAC-reported job tasks, adapting the AIOE index of Felten et al. (2021)to U.S. worker-level data and extending it globally. Previous studies measured AI exposure based on occupational tasks (Gmyrek et al., 2025; Septiandri et al., 2024; Webb, 2020) or abilities (Felten et al., 2021), but their occupation-level estimates did not vary across countries. 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. Although Felten et al. (2021) predate the emergence of generative AI, their exposure measure captures expectations of AI progress and is highly correlated with occupational exposures to generative AI (Eloundou et al., 2024), supporting the relevance of our country-specific measure for understanding disparities in AI exposure across development stages.

Second, we document substantial heterogeneity in workers' AI exposure across countries and occupations. In most occupations, AI exposure increases with countries' GDP per capita, with the development gradient most pronounced in high-skilled, cognitive occupations, such as managers and professionals. Clerical occupations emerge as the only group with AI exposure decreasing noticeably with development level, reflecting the

declining role of structured, information-processing tasks. Merging these AI exposure estimates with occupational composition data, we find that adjusting for within-occupation task variation amplifies cross-country disparities in AI exposure, since within-occupation task differences contribute as much to the cross-country variation as differences in occupational structures. Moreover, workers most exposed to AI – the top quartile of the global AI exposure distribution – are concentrated in high-income countries, while the least exposed workers – the bottom quartile – are predominantly in low- and middle-income economies. Our findings suggest that high-income countries are likely to experience the most significant short-term effects of AI. They also imply that previous studies that did not account for cross-country differences in occupational tasks (Cazzaniga et al., 2025; Gmyrek et al., 2025; Pizzinelli et al., 2023) overestimated AI exposure of workers in low- and middle-income countries.

Third, we identify key drivers of cross-country differences in task-driven AI exposure. ICT intensity, measured as the likelihood of using a computer at work at the country–sector level that is substantially higher in developed economies, is positively associated with exposure and accounts for 30–50% of global variance in AI exposure. 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).

Human capital also plays a key role, albeit smaller, as it explains about 15% of global AI exposure variation. Going beyond literature that measures human capital with workers' educational attainment or years of schooling, either in the context of economic development (reviewed by Rossi, 2020) or skill-biased technological change (Goldin and Katz, 2010), we incorporate workers' cognitive skill measures, specifically literacy proficiency, that allow us to capture international differences in education quality (Hanushek and Woessmann, 2012). We show that both education and workers' 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. Finally, stronger integration in the global economy—measured by forward linkages in global value chains and FDI inflows—is negatively associated. 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., 2025; Pizzinelli et al., 2023).

We acknowledge that the 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; Hanushek and Woessmann, 2012; 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.

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 research on occupational task content and demands (Acemoglu and Autor, 2011; Felten et al., 2021), 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. It has been applied to both measuring adult skills and their returns (Hanushek et al., 2015) as well as quantifying workers' task content and skill use at work (Caunedo et al., 2023; de la Rica et al., 2020; Lewandowski et al., 2022). PIAAC was conducted 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 31 countries, 27 of which also participated in the first cycle, with occupational information at the 2-digit ISCO-08 level. We accessed the PIAAC data through the OECD Remote Code Execution service.

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. STEP's module on task content and skill use at work aligns with PIAAC. 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 contain a task module harmonised with PIAAC and STEP.

Our final sample is a cross-country, worker-level dataset covering 54 economies at different development levels (Appendix Table A3). Because STEP excludes rural areas, we omit ISCO 6 (skilled agricultural workers and farmers) in all countries for consistency. 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.[1] To extend this framework globally, we start by replicating the Felten et al. (2021) index across 2-digit ISCO occupations in the U.S. using PIAAC survey questions instead of O*NET abilities. First, we select 35 O*NET abilities that are strongly related to AI capabilities according to Felten et al. (2021) and at the same time can be proxied with PIAAC survey questions.[2] Table 2 enlists these abilities and their AI exposures, while Appendix

[1] 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.

[2] We exclude O*NET abilities with below-median AI exposure (0.60) and below-median correlation between O*NET abilities and the PIAAC fitted values across 2-digit ISCO occupations (0.36). The AIOE variant that uses these selected 35 abilities

Table A1 provides definitions. Second, we identify PIAAC survey questions that best approximate the distribution of each ONET ability across 2-digit ISCO occupations in the U.S., regressing the occupational relevance of each ability on PIAAC questions using U.S. PIAAC data:

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

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. The dependent variable, $Y_{j,o}$, varies at the occupation level, while explanatory variables vary at the worker level.

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 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). To ensure reliability, we use 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 B1–B6 report the estimated coefficients.

For each of 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. We then compute worker-level AI exposure (AIE_{io}) as

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

where A_j is the AI exposure score of ability j from Felten et al. (2021), and Y_o is the number of relevant abilities in occupation o. Because the PIAAC, STEP, and CULS surveys provide harmonised worker-level data for 54 countries, applying equation (2) provides country-specific measures of AI exposure that incorporate international variation in job tasks and skill use at work.[4] Applying these coefficients to relevant survey data in other countries, we obtain country-specific, worker-level AI exposure measures for 54 countries. We standardise all exposure scores using the U.S. mean and standard deviation, so that a value of zero corresponds to the average U.S. worker and cross-country differences are expressed in units of U.S. dispersion.

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is virtually identical to the original AIOE of Felten et al. (2021) based on 52 abilities – the correlation between the two is 0.98 (Appendix Figure B1), validating our approach.

[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 likely negligible since the use of AI in that period was relatively low (Acemoglu et al., 2022).

[4] We maintain the highest possible level of comparability between PIAAC and STEP / CULS. The Appendix Tables B7-B12 provide the coefficients estimated for STEP/ CULS data.

Table 1. The list of PIAAC task items and full wording of survey questions, by category.

	Management & autonomy	
Q1	Supervision	Do you manage or supervise other employees?
Q2	Task sequencing	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	Planning	How often does your job usually involve planning your own activities?
Q4	Organising time	How often does your job usually involve organising your own time?
	Collaboration & Communication	
Q5	Teamwork	In your job, what proportion of your time do you usually spend cooperating or collaborating with co-workers?
Q6	Speeches / presentations	How often does your job usually involve making speeches or giving presentations in front of five or more people?
	Problem solving vs. Physical work	
Q7	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.
Q8	Sustained physical work	How often does your job usually involve working physically for a long period?
	Reading & Documentation	
Q9	Newspapers	In your job, how often do you usually read articles in newspapers, magazines or newsletters?
Q10	Professional texts	In your job, how often do you usually read articles in professional journals or scholarly publications?
Q11	Manuals	In your job, how often do you usually read manuals or reference materials?
Q12	Financial statements	In your job, how often do you usually read bills, invoices, bank statements or other financial statements?
Q13	Forms	In your job, how often do you usually fill in forms?
	Numeracy	
Q14	Prices / budgets	In your job, how often do you usually calculate prices, costs or budgets?
Q15	Advanced mathematics / statistics	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?
	Digital use	
Q16	Email	In your job, how often do you usually use email?
Q17	Spreadsheets	In your job, how often do you usually use spreadsheets, for example Excel?
Q18	Programming	In your job, how often do you usually use a programming language to program or write computer code?

Source: own elaboration.

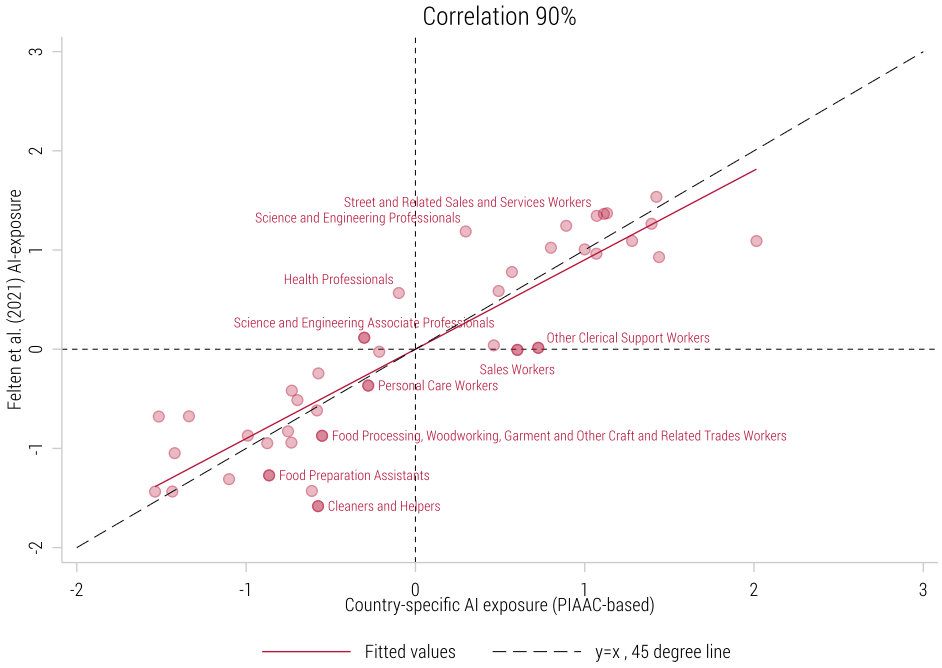
Table 2. The mapping between O*NET abilities used by Felten et al. (2021) to calculate AI exposure and PIAAC questions we use to approximate particular O*NET abilities with the US PIAAC data

Task category	Ability:	Ability-level exposure (Felten et al. 2021)	PIAAC questions used to approximate a given O*NET ability
Management & autonomy	Category flexibility	0.77	Q3, Q6, Q4, Q7, Q15, Q16
	Information ordering	0.88	Q3, Q7, Q16
Collaboration & Communication	Auditory attention	0.66	Q6, Q8, Q9
	Hearing sensitivity	0.62	Q2, Q3, Q6, Q8, Q9, Q10, Q12, Q14
	Oral comprehension	0.67	Q3, Q6, Q16
	Oral expression	0.64	Q3, Q6, Q16
	Speech clarity	0.61	Q3, Q6, Q16
	Speech recognition	0.64	Q6, Q13, Q16
Problem solving vs. Physical work	Arm-hand steadiness	0.35	Q6, Q12, Q16
	Deductive reasoning	0.73	Q3, Q6, Q7, Q16
	Dynamic strength	0.27	Q2, Q3, Q4, Q6, Q7, Q12, Q13, Q16
	Extent flexibility	0.27	Q1, Q3, Q4, Q6, Q7, Q12, Q13, Q16
	Fluency of ideas	0.61	Q3, Q6, Q16
	Gross-body coordination	0.31	Q2, Q3, Q4, Q6, Q7, Q12, Q13, Q16
	Inductive reasoning	0.71	Q3, Q4, Q6, Q7, Q13, Q16
	Originality	0.52	Q3, Q6, Q16
	Problem sensitivity	0.64	Q1, Q3, Q4, Q6, Q7, Q11, Q13, Q16
	Response orientation	0.62	Q1, Q2, Q3, Q4, Q6, Q12, Q14, Q16
	Spatial orientation	0.60	Q2, Q3, Q4, Q6, Q7, Q14, Q16, Q18
	Speed of closure	0.72	Q1, Q3, Q4, Q6, Q7, Q11, Q13, Q16
	Speed of limb movement	0.79	Q2, Q3, Q4, Q6, Q7, Q12, Q13, Q16
	Stamina	0.32	Q2, Q3, Q4, Q6, Q7, Q12, Q13, Q16
	Static strength	0.28	Q2, Q3, Q4, Q6, Q7, Q12, Q13, Q16
	Visualization	0.62	Q7, Q8, Q10, Q11, Q12, Q14, Q15, Q18
Reading & Documentation	Flexibility of closure	0.78	Q3, Q7, Q11, Q13, Q15, Q16
	Memorization	0.84	Q3, Q6, Q7, Q16
	Near vision	0.57	Q3, Q4, Q7, Q13, Q16
	Perceptual speed	0.76	Q7, Q10, Q11, Q13, Q14, Q15, Q16, Q18
	Visual colour discrimination	0.62	Q2, Q5, Q6, Q8, Q9, Q10, Q12, Q14
	Written comprehension	0.64	Q3, Q6, Q16
	Written expression	0.62	Q3, Q6, Q16
Numeracy	Mathematical reasoning	0.63	Q1, Q3, Q4, Q6, Q7, Q15, Q16, Q18
	Number facility	0.63	Q7, Q10, Q17
Digital use	Selective attention	0.75	Q7, Q11, Q13, Q15, Q16, Q18
	Timesharing	0.27	Q1, Q5, Q7, Q9, Q10, Q11, Q13, Q16

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

We assess the validity of our measure by comparing its distribution across US occupations with two established indices. 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 0.90 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 0.91 (Appendix Figure B2).[5]

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.

2.3. Econometric methodology

Explaining cross-country differences in AI exposure

We examine how differences in technology use, workforce skills, occupational composition, and firm characteristics relate to AI exposure across countries. Our analysis uses worker-level regressions that account for four groups of factors. Specifically, we estimate OLS regressions of the form:

$$AIE_{ijsc} = \beta_0 + \beta_T T_{sc} + \beta_H H_{ijsc} + \tau_o + \beta_G G_{sc} + \beta_D D_c + \delta_c^{2022} + \varepsilon_{ijsc} \quad (3)$$

[5] 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.

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, G_{sc} denotes global value chain participation and firm characteristics in sector s in country 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.
- Globalisation measures include forward and backward participation in global value chains (GVCs) complemented with firm characteristics (the share of firms with websites, those using foreign-licensed technology, those holding internationally recognised quality certificates). All are defined at the country–sector level based on ISIC Rev.4, with 1-digit ISIC sector fixed effects.[6]
- 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 indicators of human capital (learning-adjusted years of schooling, the Human Capital Index, and tertiary enrolment rate) and technological advancement (ICT Development Index and Digital Readiness Score).[7]

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.

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:

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

[6] 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.

[7] 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 / CULS
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 (internet usage, mobile cellular subscriptions, and cloud services) and infrastructure (fixed broadband subscriptions, households' internet access, secure internet services, and mobile broadband subscriptions)	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
GVC participation: backward (the share of imported inputs used in export production) and forward (domestic value added in other countries' exports) and exports	EORA (Lenzen et al., 2013, 2012)
Infrastructure	
Share of population with access to electricity	WDI
Development	
GDP per capita (natural logarithm)	WDI

Source: own elaboration.

Predicting AI Exposure for Countries Without Task Survey Data

Comparable worker-level task surveys remain unavailable for many countries, particularly low- and middle-income economies. To extend geographical coverage, we estimate the relationship between occupational AI exposure and observable national characteristics in countries with survey data, then use these relationships to predict exposure elsewhere.

To this aim, we use 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 (Table 4).

We estimate prediction models for each 1-digit ISCO occupational group, selecting the optimal specification using a stepwise variable selection procedure (Appendix C). Each estimation sample includes 82 country-cycle observations from 54 countries: 28 observed in both survey cycles, 22 observed only in the first cycle, and four observed only in the second. Control variables correspond to the year of data collection for each country.

We predict occupational AI exposure for 54 additional countries—mainly low- and middle-income economies (Appendix Table A3)—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 (and GDP per capita squared), the share of the population aged 15–64, internet use, harmonised test scores, and log exports (Table 4). 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.

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		X		X		
Time trend (2022-2023)	X	X	X	X	X	X	X	X
Human Capital Index	X				X			
Compulsory education		X						
Harmonised test scores	X	X	X					
Learning-adjusted years of schooling					X			X
University enrolment						X	X	
Survival rate from age 15-60				X				X
Share of population aged 15-64	X		X			X	X	
Population share with electricity		X						
Internet use	X					X		
Technology Infrastructure				X	X			
GVC participation						X	X	X
ICT imports				X	X		X	
Foreign direct investments								X
Exports		X	X				X	X

Notes: ICT development index, Digital Readiness Index, school enrolment rate, technology adoption, and foreign direct investments were tested but not selected for any model.

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

3. Results

3.1. Cross-country differences in task-adjusted AI exposures

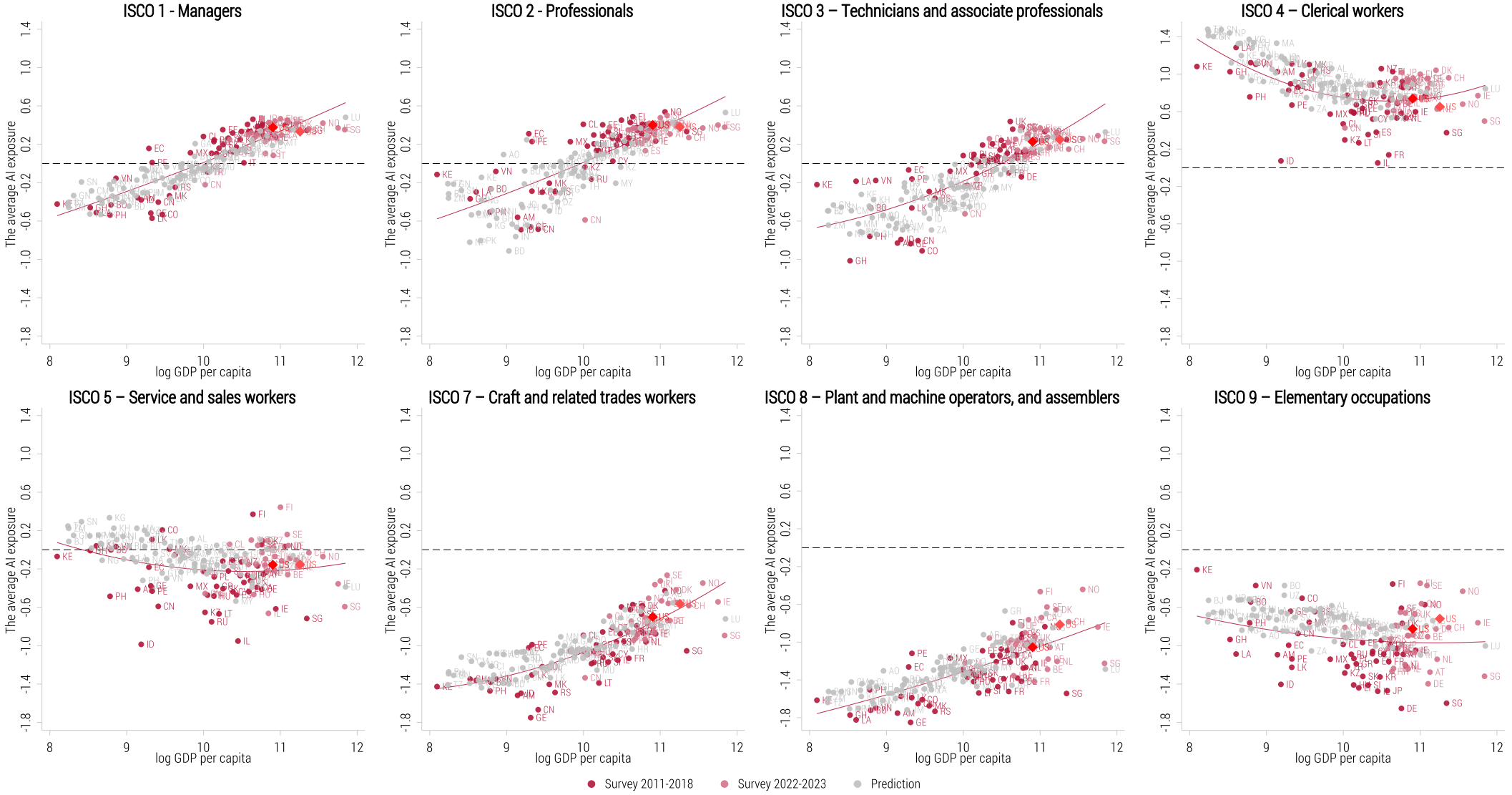
We combine survey-based estimates of AI exposure for 54 countries (27 of them with two waves of PIAAC data) with regression-based predictions for 54 additional countries lacking task survey data. Merging exposure estimates with the latest occupational structure data from ILOSTAT, we obtain a dataset covering 99 countries representing roughly 89% of global employment.[8] Appendix Table A3 lists all countries and their classification into high-income (HICs), upper-middle-income (UMICs), and low- and lower-middle-income (LMICs) groups following the World Bank classification. While occupational 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 substantial cross-country variation (Figure 2). It is particularly large 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. In contrast, among middle-skilled occupations (ISCO 4-5), AI exposure declines with GDP per capita, reflecting specialisation of less developed countries in cognitive tasks that require moderate skill levels and can be performed by AI. Across all income groups, clerical workers consistently show the highest AI exposure levels, but those in LMICs, such as call-centre workers in the Philippines, exhibit the highest AI exposure levels globally. This suggests that clerical workers may face the most widespread global impact from AI adoption. Among services and sales workers (ISCO 5), AI exposure also declines with GDP per capita but less steeply, and the exposure levels are visibly lower than among clerical workers.

Low-skilled occupations (ISCO 7-9) are generally less exposed to AI than the other occupational groups. Their exposure levels remain negative, that is, below our benchmark of the US average (Figure 5). Among craft and related trades workers (ISCO 7) and plant and machine operators (ISCO 8), AI exposure increases modestly with development, likely reflecting an increasing use of digital technologies and tools among such workers in more developed countries. Elementary occupations (ISCO 9) exhibit substantial cross-country variation but a modest development gradient.

[8] 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 (99) is smaller than the sample size of countries with AI exposures (108).

Figure 2. Country-specific occupational AI exposures, by ISCO-1d occupational groups

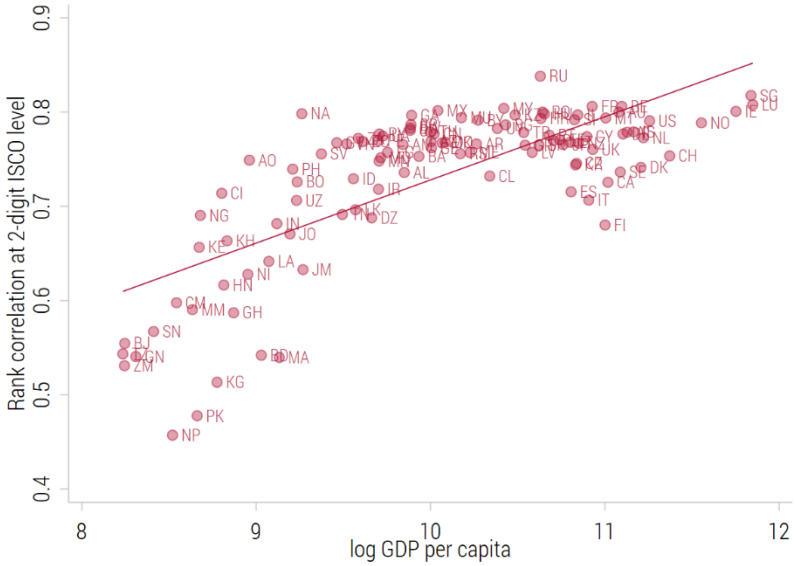


Note: Survey 2011-2018 includes the first cycle of PIAAC, STEP and 2016 CULS surveys. Survey 2022-2023 includes the second cycle of PIAAC and CULS 2023 surveys. The values of the AI exposures are standardised with the US mean and standard deviation. For average AI exposures by Felten et al. (2021), see Appendix Figure B5.

Source: Own calculations based on PIAAC, STEP, WB, EORA, ITU, CISCO, and Felten et al. (2021) data.

These pronounced cross-country differences in occupational tasks have three important consequences for understanding AI exposure in more and less developed countries. First, the lower the development level of a country, the less similar the occupational rankings of AI exposure based on the country-specific measures and the AIOE of Felten et al. (2021). The within-country rank correlations between these measures increase with GDP per capita, from 0.5-0.6 in LMICs to 0.8 in HICs (at the 2-digit ISCO occupation level, Figure 3).

Figure 3. The rank correlation between the country-specific AI exposure and AIOE of Felten et al. (2021), across 2-digit ISCO occupations, against GDP per capita.

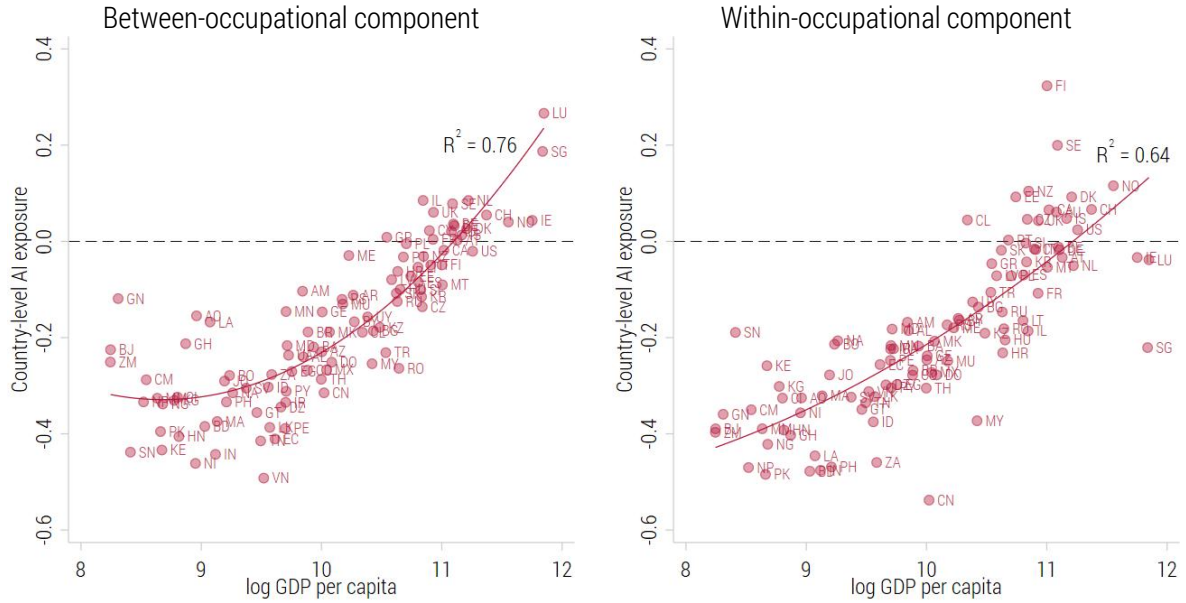


Source: own elaboration based on PIAAC, STEP, CULS, ILOSTAT, and Felten et al. (2021) data.

Second, international differences in occupational structures and differences in occupational tasks have comparable contributions to the global variation in countries' AI exposure (Figure 4). Less developed countries tend to exhibit higher shares of occupations less exposed to AI, which reduces their AI exposure as compared to high-income countries, such as the U.S. (left panel of Figure 4). However, workers in these countries also tend to perform tasks less exposed to AI, which reduces these countries' AI exposure to a similar extent (right panel of Figure 4). Using a covariance-based decomposition (Morduch and Sicular, 2002), we attribute 60% of the cross-country variance in AI exposure to differences in occupational tasks, 54% to differences in occupational structures, and -14% to the interaction effect (shown in Appendix Figure B3).[9] Hence, applying the AI exposure measurements from the U.S. or other high-income countries globally under the assumption that occupational exposures are identical worldwide would substantially overestimate AI exposure in less developed countries and would underestimate the variation across the development spectrum.

[9] The negative contribution of the interaction effect to the cross-country variance results from this effect being positive in most LMICs (Appendix Figure B4). This in turn reflects the fact that LMICs' shares of occupations with AI exposures being noticeably lower than those of comparable occupations in HICs, such as managers and professionals, are also noticeably lower in in HICs.

Figure 4. The decomposition of country-level average AI exposure into the contribution of country-specific occupational structure and country-specific occupational tasks



Note: the between- and within-occupational components are calculated with a standard shift-share decomposition, using the U.S. cycle 1 PIAAC as a reference. Appendix Figure B3 shows the interaction effect that completes the decomposition.

Source: Own calculations based on the O*NET, PIAAC, STEP, CULS and Felten et al. (2021) data.

Third, the allocation of workers who are highly exposed to AI and those who are barely exposed to AI is strongly polarised across the development spectrum. We define the least exposed and most exposed workers as those, respectively, in the bottom and top quartiles of the global distribution of country-specific occupational AI exposure, weighted by the shares of country-occupation cells in global employment. High-income countries account for 50.0% of the world's most AI-exposed workers but only 6.0% of the least exposed, despite representing just 24.5% of global employment (Table 5). In upper-middle-income countries, including Brazil, China, and Türkiye, this disparity reverses: UMICs host 23.7% of the most exposed and almost as much of the least exposed (28.4%), slightly below their 34.0% share of global employment. In contrast, LMICs, including India, Indonesia, the Philippines, and many African countries, account for 26.2% of the most exposed but more than twice as much (65.6%) of the least exposed workers—well above their 41.5% employment share.

Table 5. 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	High-income
Most exposed (top 25%)	26.3	23.7	50.0
Least exposed (bottom 25%)	65.6	28.4	6.0
Total employment	41.5	34.0	24.5

Note: Country group classifications follow Appendix Table A3.

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

3.2. Drivers of task-adjusted AI exposure

To identify key drivers of AI exposure, we estimate worker-level regressions based on Equation (2), using survey data for 67 country-years with all required controls available (24 countries covered in both survey cycles, 17 – only in the first cycle, and two – only in the second). We estimate regressions without occupational fixed effects to capture drivers of overall differences (column 1 of Table 6), and with occupational (2-digit ISCO) fixed effects to capture relationships within occupations (columns 2–5 of Table 6).

Access to digital technologies is strongly and positively associated with AI exposure. Allowing for a non-linear relationship, we find it to be especially strong in country–sectors where over 60% of workers use computers (Appendix Figure B4). A 17 pp increase in computer use— comparable to the difference between the U.S. (75%) and China (58%)—raises average AI exposure by 0.10, equivalent to 13% of the U.S.–China gap. The relationship between ICT intensity and AI exposure is most pronounced among workers in middle-skilled occupations (ISCO 4–5), and the weakest among workers in high-skilled occupations (ISCO 1–3) who use computers at work more often than other groups (Appendix Figure B4) but perform less routine-intensive tasks.

Human capital, as measured by education and literacy proficiency, is significantly and positively associated with AI exposure, even within occupations. Controlling for occupational differences, workers with primary education have substantially lower exposure (−0.25), while tertiary-educated workers have higher exposure (+0.21), relative to secondary-educated workers. Moreover, a worker at the highest literacy level (4–5) has, on average, an AI exposure score 0.17 points higher than a comparable worker at the medium proficiency level (2), which is comparable to the difference between the average manager (ISCO 1) and craft and related trade worker (ISCO 7) in the U.S. The differences related to higher literacy levels are larger in manual (ISCO 7–9) and clerical occupations (ISCO 4–5) than in high-skilled occupations (ISCO 1–3) that generally require higher levels of cognitive skills. 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 more often work in occupations exposed to AI (Cazzaniga et al., 2025; Pizzinelli et al., 2023), but our worker-level approach demonstrates this relationship also holds within occupations. Since skill-related effects weaken once occupational controls are included (compare Columns 1 and 2-5 of Table 6), part of human capital's influence operates through occupational structure.

Occupational sorting masks substantial gender differences. Women have higher AI exposure in the specification without occupational controls (+0.08), but significantly lower exposure when occupations are controlled for (−0.17). The within-occupation gender gap is largest in manual occupations (ISCO 7–9, −0.289), followed by clerical and service occupations (ISCO 4–5, −0.231). We also find that AI exposure peaks among prime-aged workers. Workers aged 35–44 have the highest AI exposure, while both younger and older workers are less exposed, particularly those aged 16-24 and 55-64. Again, these differences persist within occupations.

Global value chain (GVC) participation appears to be related to AI exposure mostly through occupational structures. In countries with average GDP per capita in our sample—such as the United Kingdom or Finland—greater GVC participation is associated with lower AI exposure, but the relationship becomes more positive with GDP per capita (column 1 of Table 6). However, it is mostly insignificant after controlling for occupational fixed effects (columns 2–5 of Table 6). Finally, AI exposure has increased over time, particularly in middle- and lower-skilled occupations, suggesting a narrowing of exposure differences between occupational groups.

Table 6. The correlates of task-adjusted, worker-level AI exposures (OLS)

Variable	(1) All workers	(2) All workers	(3) ISCO 1–3	(4) ISCO 4–5	(5) ISCO 7–9
ICT intensity	0.019	-0.346	0.271	-1.477**	-0.665**
	(0.308)	(0.263)	(0.302)	(0.611)	(0.319)
ICT intensity²	0.720***	0.929***	0.170	2.074***	1.240***
	(0.220)	(0.189)	(0.211)	(0.451)	(0.257)
Education: Primary	-0.382***	-0.247***	-0.245***	-0.327***	-0.174***
	(0.018)	(0.014)	(0.021)	(0.026)	(0.015)
Education: Tertiary	0.370***	0.209***	0.174***	0.260***	0.193***
	(0.016)	(0.010)	(0.009)	(0.020)	(0.021)
Low literacy proficiency (levels 1 or lower)	-0.252***	-0.162***	-0.102***	-0.173***	-0.187***
	(0.016)	(0.013)	(0.015)	(0.022)	(0.019)
Medium literacy proficiency (level 3)	0.147***	0.087***	0.066***	0.101***	0.116***
	(0.011)	(0.008)	(0.007)	(0.022)	(0.015)
High literacy proficiency (levels 4 and 5)	0.172***	0.096***	0.082***	0.135***	0.182***
	(0.015)	(0.012)	(0.008)	(0.032)	(0.037)
Gender: Woman	0.081***	-0.175***	-0.094***	-0.231***	-0.289***
	(0.015)	(0.010)	(0.006)	(0.023)	(0.019)
Age: 16-24	-0.330***	-0.301***	-0.319***	-0.397***	-0.224***
	(0.029)	(0.025)	(0.025)	(0.049)	(0.023)
Age: 25-34	-0.041***	-0.032***	-0.018***	-0.040**	-0.070***
	(0.010)	(0.008)	(0.007)	(0.019)	(0.017)
Age: 45-54	-0.043***	-0.040***	-0.006	-0.068***	-0.064***
	(0.009)	(0.007)	(0.007)	(0.019)	(0.014)
Age: 55-65	-0.099***	-0.105***	-0.062***	-0.147***	-0.129***
	(0.012)	(0.009)	(0.008)	(0.022)	(0.017)
Forward GVC participation (GVCF) exports share	-0.208**	-0.117	-0.090	0.089	-0.155*
	(0.090)	(0.094)	(0.057)	(0.228)	(0.093)
GVCF share (std.) * [Ln(GDP pc) – mean(Ln(GDP pc)]	0.509**	0.509***	0.354*	0.913**	0.113
	(0.223)	(0.196)	(0.183)	(0.463)	(0.268)
Backward GVC participation (GVCB) exports share	-0.290***	-0.056	0.005	0.204**	-0.238***
	(0.092)	(0.052)	(0.047)	(0.099)	(0.072)
GVCB share (std.) * [Ln(GDP pc) – mean(Ln(GDP pc)]	0.580***	0.102	0.045	-0.515**	0.198
	(0.156)	(0.099)	(0.090)	(0.226)	(0.148)
Ln(GDP per capita) –mean(Ln(GDP per capita))	-0.181**	-0.213***	-0.048	-0.416***	-0.214**
	(0.087)	(0.075)	(0.055)	(0.132)	(0.099)
Time trend (secular change between 2010s and 2020s)	0.061***	0.094***	0.019	0.133***	0.178***
	(0.018)	(0.016)	(0.017)	(0.033)	(0.026)
2-digit ISCO occupation fixed effects	N	Y	Y	Y	Y
Observations	**234358**	**234358**	**109895**	**64532**	**59931**

Notes: All specifications include 1-digit ISIC Rev. 4 sector fixed effects and their interactions with GDP per capita, and country-sector shares of firms with a website, of firms using licensed foreign technology, and of firms with an international quality certificate. Men, secondary education, ages 25–34, and literacy level 2 are reference categories. Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

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

Next, using the estimated coefficients and covariance-based decomposition (Equation 3), we quantify the contribution of each explanatory variable to cross-country variation in AI exposure. 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 86-88% of the cross-country variance in AI exposure (Table 7). Across all specifications, occupational structure explains about 22% of variance, indicating that almost 80% of cross-country differences in AI exposure reflect within-occupation task compositions.[10] Among drivers of these within-occupation gaps, ICT intensity contributes the most (29–50% of explained variance), followed by human capital (15–16%), with literacy proficiency alone contributing about 8% (detailed results available upon request). The contributions of human capital and occupational structure are stable across specifications. Global value chains contribute very little (0–3%), while the secular shift in AI exposure over time adds 6–8%.

The small contribution of GDP per capita (1.7%, Table 7) in models that control for ICT intensity, human capital, occupational composition, and other structural factors suggests that GDP per capita captures AI exposure primarily through its correlation with ICT adoption and human capital rather than through any independent income effect or other omitted factors correlated with GDP per capita. The contribution turns higher when GDP is replaced with indicators of human capital that capture differences in schooling quality (Human Capital Index, learning-adjusted years of schooling), but it is not the case with tertiary enrolment. This suggests that capturing quality-adjusted skill supply is key for understanding differences in AI exposure across the development spectrum. Although the relative importance of ICT intensity declines in specifications that control for quality-adjusted human capital, its contribution remains larger than the total contribution of human capital. Replacing GDP per capita with indicators of technological capabilities (ICT development index, Digital Readiness Index) does not increase the explanatory power of the model, but it confirms the key role of ICT intensity.

Table 7. The decomposition of the cross-country variance in country-specific AI exposure (in % of variance)

Occupational structure	ICT intensity	Human capital	Global value chains	Development indicator	Time trend	Explained variance	Development indicator used:
21.7	40.8	15.6	1.5	1.7	6.3	87.5	GDP per capita (log)
21.6	50.3	16.0	-0.1	-8.5	6.7	85.9	ICT development index
21.6	38.6	15.6	0.8	2.1	7.9	86.5	Digital Readiness Index
21.6	29.4	15.4	0.9	13.0	7.7	88.1	Human Capital Index
21.6	30.3	15.4	2.0	11.1	7.7	88.2	Learning-adjusted years of schooling
21.7	35.7	15.6	3.2	3.6	7.2	87.0	Tertiary education enrolment rate

Note: variance-covariance decomposition (Morduch and Sicular, 2002) applied to estimates shown in column 2 of Table 6.
Source: Own estimates based on PIAAC, STEP, WB, EORA, ITU and CISCO data.

[10] The share attributed to occupational structures is lower than in the shift-share decomposition (Figure 4) since the estimation sample includes mostly high- and middle-income countries with less diverse occupational structures.

Overall, our results underscore the central role of ICT penetration 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).

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 construct a worker-level indicator of AI exposure by adapting AIOE to U.S. PIAAC data on job tasks. We then extend this approach to 54 countries with comparable survey data and generate regression-based predictions for 54 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 across development stages. The disparity is most evident among high-skilled occupations, where workers perform abstract, non-routine cognitive tasks that vary substantially across countries depending on technological capacity, skill supply, and integration into global value chains (Caunedo et al., 2023; Lewandowski et al., 2022). Clerical workers emerge as the only occupational group where workers in less developed countries are noticeably more exposed to AI than those in advanced economies, reflecting less developed countries' specialisation in functions such as call centres. Clerical workers are also more exposed to AI than other occupational groups, suggesting their jobs may be affected by AI more profoundly than others. Among other occupations that require more manual tasks, such as sales and service, craft and related trade workers, or plant and machine operators, AI exposure is visibly lower, and its gradient across development stages is less pronounced.

In consequence, cross-country differences in occupational task content are as important for understanding differences in workers' AI exposure across the development spectrum as the differences in occupational structures. Moreover, the occupational rankings of AI exposure in less developed countries differ substantially from those in high-income countries. Finally, at the global level, high-income countries employ the largest share of workers in highly AI-exposed jobs, while low-income countries are notably overrepresented in employing the least exposed workers.

Using regression-based decompositions, we attribute most of cross-country variation in AI exposure, especially that observed across workers in comparable occupations, to differences in ICT intensity and technological capability, followed by human capital. 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.

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 used to calculate AI exposures and 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.

Source: own elaboration based on O*NET data.

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: Allocation of countries to income groups

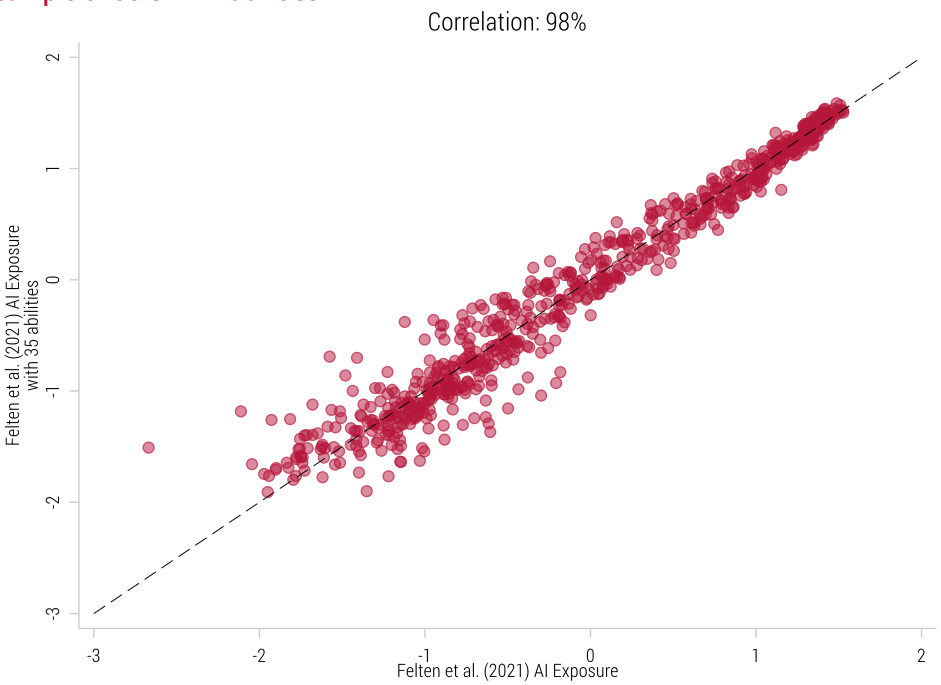
Low- and Lower Middle-Income	Upper Middle-Income	High-Income
Covered by survey data		
Armenia (STEP), Bolivia (STEP), Georgia (STEP), Ghana (STEP), Indonesia (PIAAC 1), Kenya (STEP), Laos (STEP), Philippines (STEP), Sri Lanka (STEP), Vietnam (STEP)	China (CULS), Colombia (STEP), Ecuador (PIAAC 1), Kazakhstan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

Notes: Survey 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. 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.

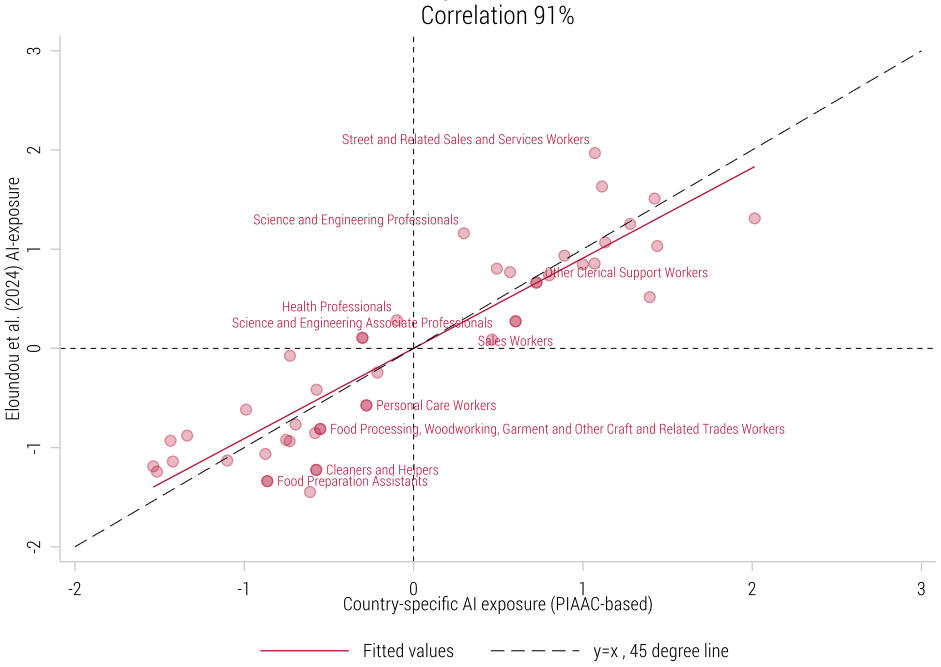
Appendix B – Additional results

Figure B1. Correlation between the AIOE of Felten et al. (2021) and the AIOE variant calculated with a restricted sample of 35 O*NET abilities



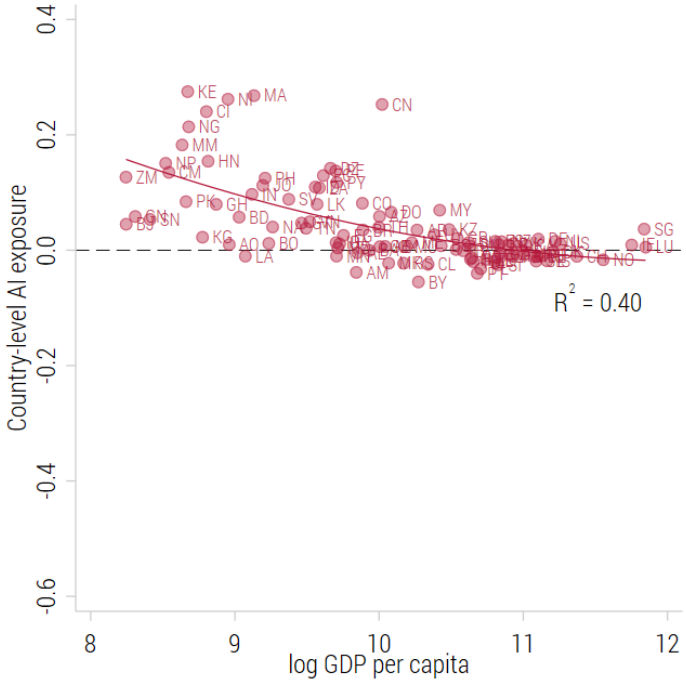
Notes: 6-digit occupations in the SOC10 classification.
Source: own elaboration based on Felten et al. (2021).

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



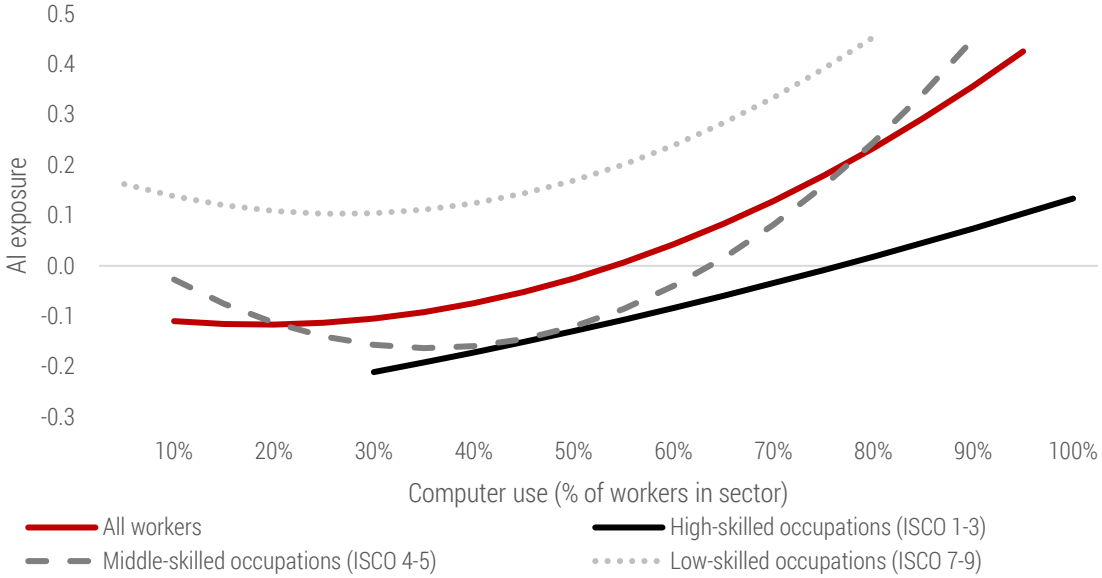
Note: We use GPT exposures based on human ratings (Eloundou et al., 2024).
Source: own elaboration based on Eloundou et al. (2024) and PIAAC data.

Figure B3. The contribution of the interaction between country-specific occupational structures and country-specific occupational tasks to country-level average AI exposure



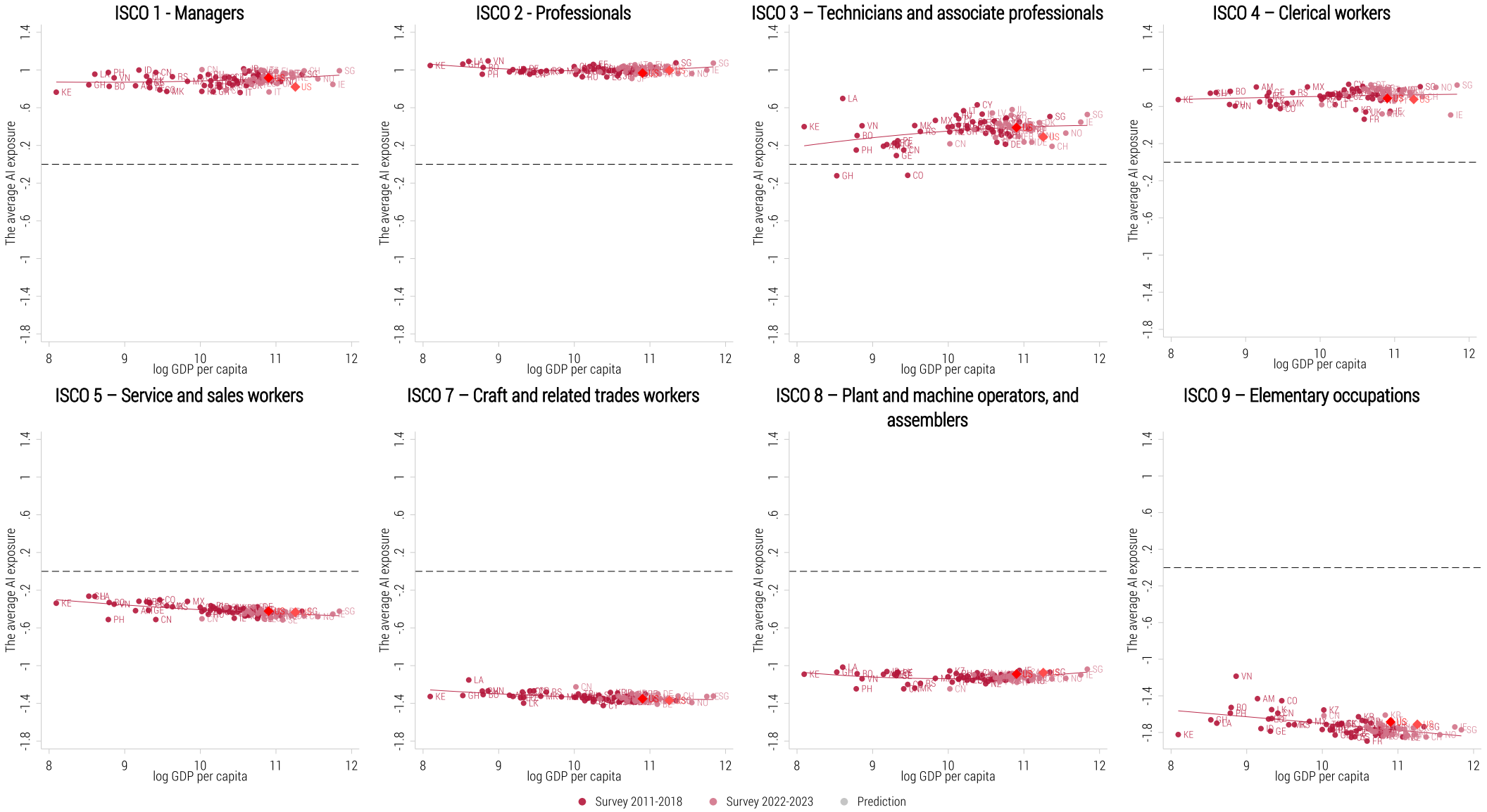
Note: calculated with a standard shift-share decomposition, using the U.S. cycle 1 PIAAC as a reference. Figure 3 shows the between-occupation and the within-occupation components.
Source: own elaboration based on PIAAC, STEP, CULS, ILOSTAT, and Felten et al. (2021) data.

Figure B4. Estimated relationship between computer use and AI exposure, overall and by occupational groups



Note: Based on the estimates presented in Columns 2-5 of Table. For each category, 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.

Figure B5. The AI exposure by Felten et al. (2021) in countries covered by PIAAC, STEP, and CULS survey data, by ISCO-1d occupational groups



Note: The values of the AI exposures are standardised with the US mean and standard deviation.
Source: Own calculations based on PIAAC, STEP, and Felten et al (2021) data.

Table B1. 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
Email						
Less than once a month	0.144***		0.045***	0.086***	-0.018***	-0.027***
	(0.011)		(0.006)	(0.009)	(0.004)	(0.006)
Less than once a week but at least once a month	0.147***		0.045***	0.087***	-0.016***	-0.026***
	(0.012)		(0.007)	(0.010)	(0.005)	(0.007)
At least once a week but not every day	0.124***		0.047***	0.091***	-0.026***	-0.044***
	(0.007)		(0.004)	(0.006)	(0.003)	(0.004)
Every day	0.048***		0.048***	0.103***	-0.062***	-0.092***
	(0.004)		(0.002)	(0.003)	(0.002)	(0.003)
Complex problems						
Less than once a month			0.121***	0.180***	0.035***	0.053***
			(0.003)	(0.004)	(0.002)	(0.003)
Less than once a week but at least once a month			0.114***	0.174***	0.028***	0.046***
			(0.003)	(0.004)	(0.002)	(0.003)
At least once a week but not every day			0.120***	0.182***	0.028***	0.049***
			(0.003)	(0.004)	(0.002)	(0.003)
Every day			0.122***	0.181***	0.031***	0.054***
			(0.003)	(0.005)	(0.002)	(0.004)
Planning						
Less than once a month			0.033***	0.101***	0.002	0.011***
			(0.004)	(0.005)	(0.003)	(0.004)
Less than once a week but at least once a month			0.018***	0.091***	0.005	0.016***
			(0.005)	(0.006)	(0.003)	(0.005)
At least once a week but not every day			0.018***	0.095***	0.003	0.012***
			(0.004)	(0.005)	(0.003)	(0.004)
Every day			0.019***	0.100***	0.001	0.008**
			(0.003)	(0.004)	(0.002)	(0.003)
Organising time						
Less than once a month			0.112***		0.031***	0.057***
			(0.005)		(0.004)	(0.005)
Less than once a week but at least once a month			0.106***		0.025***	0.049***
			(0.005)		(0.004)	(0.005)
At least once a week but not every day			0.111***		0.026***	0.048***
			(0.004)		(0.003)	(0.004)
Every day			0.107***		0.022***	0.041***
			(0.003)		(0.002)	(0.003)
Speeches / presentations						
Less than once a month	0.045***	0.020***	0.019***	0.036***	-0.013***	-0.011***
	(0.005)	(0.002)	(0.003)	(0.004)	(0.002)	(0.003)
Less than once a week but at least once a month	0.028***	0.015***	0.018***	0.039***	-0.015***	-0.010***
	(0.006)	(0.003)	(0.003)	(0.005)	(0.002)	(0.003)

At least once a week but not every day	0.023***	0.011***	0.019***	0.039***	-0.014***	-0.008**
	(0.007)	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)
Every day	0.044***	-0.000	0.022***	0.049***	-0.014***	-0.016***
	(0.006)	(0.003)	(0.004)	(0.005)	(0.002)	(0.004)
Advanced mathematics / statistics						
Less than once a month			0.005			
			(0.004)			
Less than once a week but at least once a month			0.014***			
			(0.005)			
At least once a week but not every day			0.013**			
			(0.005)			
Every day			0.009			
			(0.006)			
Financial statements						
Less than once a month	0.056***				-0.007***	-0.006*
	(0.006)				(0.002)	(0.004)
Less than once a week but at least once a month	0.059***				-0.004	0.000
	(0.006)				(0.002)	(0.004)
At least once a week but not every day	0.064***				-0.002	0.001
	(0.005)				(0.002)	(0.003)
Every day	0.054***				-0.006***	-0.007**
	(0.005)				(0.002)	(0.003)
Sustained physical work						
Less than once a month		0.071***				
		(0.003)				
Less than once a week but at least once a month		0.083***				
		(0.003)				
At least once a week but not every day		0.095***				
		(0.002)				
Every day		0.118***				
		(0.001)				
Newspapers						
Less than once a month		0.058***				
		(0.002)				
Less than once a week but at least once a month		0.055***				
		(0.002)				
At least once a week but not every day		0.053***				
		(0.002)				
Every day		0.054***				
		(0.002)				
Forms						
Less than once a month					0.007***	0.011***
					(0.002)	(0.004)
Less than once a week but at least once a month					0.001	0.003
					(0.003)	(0.004)
At least once a week but not every day					0.005**	0.012***
					(0.002)	(0.003)

Every day					0.015***	0.027***
					(0.002)	(0.003)
Task sequencing						
Less than once a month					0.068***	
					(0.002)	
Less than once a week but at least once a month					0.062***	
					(0.002)	
At least once a week but not every day					0.057***	
					(0.002)	
Every day					0.055***	
					(0.002)	
Supervision						
No						0.072***
						(0.002)
Observations	7,106	7,099	7,093	7,096	7,084	7,089
R-squared	0.350	0.820	0.914	0.898	0.643	0.640

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on PIAAC and O*NET data.

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

VARIABLES	(7) Flexibility of closure	(8) Fluency of ideas	(9) Gross-body coordination	(10) Hearing sensitivity	(11) Inductive reasoning	(12) Information ordering
Email						
Less than once a month	0.019***	0.095***	-0.018***		0.038***	0.076***
	(0.005)	(0.007)	(0.004)		(0.008)	(0.008)
Less than once a week but at least once a month	0.024***	0.094***	-0.016***		0.047***	0.073***
	(0.006)	(0.008)	(0.005)		(0.008)	(0.008)
At least once a week but not every day	0.022***	0.102***	-0.026***		0.047***	0.076***
	(0.004)	(0.005)	(0.003)		(0.005)	(0.005)
Every day	0.015***	0.125***	-0.065***		0.058***	0.079***
	(0.002)	(0.003)	(0.002)		(0.003)	(0.003)
Complex problems						
Less than once a month	0.087***		0.035***		0.105***	0.178***
	(0.003)		(0.002)		(0.004)	(0.003)
Less than once a week but at least once a month	0.082***		0.027***		0.098***	0.174***
	(0.003)		(0.002)		(0.004)	(0.004)
At least once a week but not every day	0.086***		0.027***		0.109***	0.181***
	(0.003)		(0.002)		(0.004)	(0.003)
Every day	0.089***		0.030***		0.112***	0.184***
	(0.003)		(0.003)		(0.004)	(0.004)
Planning						
Less than once a month	0.048***	0.128***	0.002	0.018***	0.031***	0.103***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.005)	(0.005)
Less than once a week but at least once a month	0.043***	0.127***	0.004	0.016***	0.015***	0.092***
	(0.004)	(0.005)	(0.003)	(0.002)	(0.005)	(0.005)
At least once a week but not every day	0.045***	0.130***	0.003	0.012***	0.019***	0.093***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.005)	(0.004)
Every day	0.045***	0.133***	0.001	0.013***	0.022***	0.095***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
Organising time						
Less than once a month			0.033***		0.097***	
			(0.004)		(0.006)	
Less than once a week but at least once a month			0.027***		0.097***	
			(0.004)		(0.006)	
At least once a week but not every day			0.026***		0.102***	
			(0.003)		(0.005)	
Every day			0.022***		0.099***	
			(0.002)		(0.004)	
Speeches / presentations						
Less than once a month		0.048***	-0.013***	0.002	0.029***	
		(0.003)	(0.002)	(0.002)	(0.003)	
Less than once a week but at least once a month		0.052***	-0.015***	-0.003	0.028***	
		(0.004)	(0.002)	(0.002)	(0.004)	
At least once a week but not every day		0.054***	-0.014***	-0.004*	0.029***	

		(0.004)	(0.003)	(0.002)	(0.005)
Every day		0.062***	-0.014***	-0.018***	0.038***
		(0.004)	(0.003)	(0.002)	(0.004)
Advanced mathematics / statistics					
Less than once a month	0.002				
	(0.003)				
Less than once a week but at least once a month	0.010**				
	(0.004)				
At least once a week but not every day	0.010**				
	(0.005)				
Every day	0.011**				
	(0.005)				
Financial statements					
Less than once a month			-0.008***	0.000	
			(0.002)	(0.002)	
Less than once a week but at least once a month			-0.003	0.003	
			(0.002)	(0.002)	
At least once a week but not every day			-0.001	0.003	
			(0.002)	(0.002)	
Every day			-0.005***	0.001	
			(0.002)	(0.002)	
Sustained physical work					
Less than once a month				0.031***	
				(0.002)	
Less than once a week but at least once a month				0.040***	
				(0.003)	
At least once a week but not every day				0.047***	
				(0.002)	
Every day				0.066***	
				(0.001)	
Newspapers					
Less than once a month				0.013***	
				(0.002)	
Less than once a week but at least once a month				0.009***	
				(0.002)	
At least once a week but not every day				0.006***	
				(0.002)	
Every day				0.008***	
				(0.002)	
Forms					
Less than once a month	0.048***		0.007***		0.080***
	(0.003)		(0.002)		(0.004)
Less than once a week but at least once a month	0.044***		0.002		0.076***
	(0.003)		(0.003)		(0.005)
At least once a week but not every day	0.043***		0.006***		0.073***
	(0.003)		(0.002)		(0.004)
Every day	0.051***		0.017***		0.076***

	(0.002)		(0.002)		(0.003)	
Task sequencing						
Less than once a month			0.072***	0.066***		
			(0.002)	(0.002)		
Less than once a week but at least once a month			0.066***	0.062***		
			(0.002)	(0.002)		
At least once a week but not every day			0.060***	0.060***		
			(0.002)	(0.002)		
Every day			0.058***	0.061***		
			(0.002)	(0.002)		
Manuals						
Less than once a month	0.059***					
	(0.003)					
Less than once a week but at least once a month	0.055***					
	(0.003)					
At least once a week but not every day	0.056***					
	(0.003)					
Every day	0.054***					
	(0.003)					
Prices / budgets						
Less than once a month				-0.007***		
				(0.002)		
Less than once a week but at least once a month				-0.005**		
				(0.002)		
At least once a week but not every day				-0.008***		
				(0.002)		
Every day				-0.009***		
				(0.002)		
Professional texts						
Less than once a month				0.006***		
				(0.002)		
Less than once a week but at least once a month				0.006***		
				(0.002)		
At least once a week but not every day				0.009***		
				(0.002)		
Every day				0.006**		
				(0.003)		
Observations	7,096	7,102	7,084	7,086	7,092	7,099
R-squared	0.901	0.853	0.653	0.863	0.913	0.897

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on PIAAC and O*NET data.

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

VARIABLES	(13) Mathematical reasoning	(14) Memorization	(15) Near vision	(16) Number facility	(17) Oral comprehension	(18) Oral expression
Email						
Less than once a month	0.031***	0.042***	0.030***		0.191***	0.189***
	(0.005)	(0.004)	(0.008)		(0.013)	(0.012)
Less than once a week but at least once a month	0.032***	0.041***	0.035***		0.177***	0.176***
	(0.006)	(0.004)	(0.009)		(0.014)	(0.014)
At least once a week but not every day	0.037***	0.042***	0.029***		0.194***	0.194***
	(0.003)	(0.003)	(0.005)		(0.008)	(0.008)
Every day	0.070***	0.046***	0.021***		0.195***	0.199***
	(0.002)	(0.002)	(0.003)		(0.005)	(0.005)
Complex problems						
Less than once a month	0.049***	0.083***	0.138***	0.122***		
	(0.003)	(0.002)	(0.004)	(0.002)		
Less than once a week but at least once a month	0.053***	0.080***	0.129***	0.126***		
	(0.003)	(0.002)	(0.004)	(0.002)		
At least once a week but not every day	0.059***	0.083***	0.133***	0.130***		
	(0.003)	(0.002)	(0.004)	(0.002)		
Every day	0.056***	0.080***	0.136***	0.128***		
	(0.003)	(0.002)	(0.004)	(0.003)		
Planning						
Less than once a month	0.016***	0.046***	0.040***		0.263***	0.250***
	(0.003)	(0.002)	(0.005)		(0.007)	(0.007)
Less than once a week but at least once a month	0.008**	0.040***	0.019***		0.256***	0.244***
	(0.004)	(0.003)	(0.006)		(0.008)	(0.008)
At least once a week but not every day	0.008**	0.041***	0.018***		0.255***	0.243***
	(0.003)	(0.002)	(0.005)		(0.006)	(0.006)
Every day	0.012***	0.044***	0.019***		0.251***	0.241***
	(0.003)	(0.002)	(0.004)		(0.004)	(0.004)
Organising time						
Less than once a month	0.039***		0.138***			
	(0.005)		(0.007)			
Less than once a week but at least once a month	0.037***		0.128***			
	(0.004)		(0.007)			
At least once a week but not every day	0.045***		0.133***			
	(0.004)		(0.005)			
Every day	0.046***		0.128***			
	(0.003)		(0.004)			
Speeches / presentations						
Less than once a month	0.022***	0.015***			0.058***	0.059***
	(0.002)	(0.002)			(0.006)	(0.005)
Less than once a week but at least once a month	0.028***	0.016***			0.056***	0.058***
	(0.003)	(0.002)			(0.007)	(0.007)
At least once a week but not every day	0.025***	0.019***			0.057***	0.061***

	(0.003)	(0.002)			(0.008)	(0.008)
Every day	0.011***	0.037***			0.102***	0.120***
	(0.003)	(0.002)			(0.007)	(0.007)
Advanced mathematics / statistics						
Less than once a month	0.022***					
	(0.003)					
Less than once a week but at least once a month	0.034***					
	(0.004)					
At least once a week but not every day	0.029***					
	(0.005)					
Every day	0.019***					
	(0.005)					
Forms						
Less than once a month			0.094***			
			(0.004)			
Less than once a week but at least once a month			0.086***			
			(0.005)			
At least once a week but not every day			0.086***			
			(0.004)			
Every day			0.098***			
			(0.003)			
Supervision						
No	0.024***					
	(0.002)					
Professional texts						
Less than once a month				0.037***		
				(0.003)		
Less than once a week but at least once a month				0.036***		
				(0.003)		
At least once a week but not every day				0.036***		
				(0.003)		
Every day				0.035***		
				(0.003)		
Programming						
Less than once a month	0.017***					
	(0.004)					
Less than once a week but at least once a month	0.027***					
	(0.006)					
At least once a week but not every day	0.018***					
	(0.006)					
Every day	0.024***					
	(0.004)					
Spreadsheets						
Less than once a month				0.041***		
				(0.004)		
Less than once a week but at least once a month				0.042***		
				(0.003)		

At least once a week but not every day				0.057***		
				(0.003)		
Every day				0.072***		
				(0.002)		
Observations	7,090	7,096	7,095	7,101	7,102	7,102
R-squared	0.878	0.899	0.922	0.856	0.848	0.850

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on PIAAC and O*NET data.

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

VARIABLES	(19) Originality	(20) Perceptual speed	(21) Problem sensitivity	(22) Response orientation	(23) Selective attention	(24) Spatial orientation
Email						
Less than once a month	0.091***	0.020***	0.026***	-0.004	0.025***	-0.004
	(0.007)	(0.006)	(0.008)	(0.005)	(0.006)	(0.003)
Less than once a week but at least once a month	0.090***	0.025***	0.036***	-0.005	0.031***	-0.008**
	(0.008)	(0.006)	(0.008)	(0.005)	(0.007)	(0.004)
At least once a week but not every day	0.096***	0.017***	0.035***	-0.013***	0.024***	-0.012***
	(0.005)	(0.004)	(0.005)	(0.003)	(0.004)	(0.002)
Every day	0.116***	0.001	0.039***	-0.044***	0.007***	-0.029***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Complex problems						
Less than once a month		0.102***	0.082***		0.126***	0.022***
		(0.003)	(0.004)		(0.003)	(0.002)
Less than once a week but at least once a month		0.098***	0.075***		0.119***	0.021***
		(0.003)	(0.004)		(0.003)	(0.002)
At least once a week but not every day		0.099***	0.088***		0.119***	0.022***
		(0.003)	(0.004)		(0.003)	(0.002)
Every day		0.103***	0.094***		0.122***	0.023***
		(0.003)	(0.004)		(0.003)	(0.002)
Planning						
Less than once a month	0.122***		0.021***	0.004		0.000
	(0.004)		(0.005)	(0.003)		(0.002)
Less than once a week but at least once a month	0.122***		0.011**	0.012***		0.005**
	(0.004)		(0.005)	(0.004)		(0.002)
At least once a week but not every day	0.125***		0.014***	0.007**		0.002
	(0.004)		(0.005)	(0.003)		(0.002)
Every day	0.128***		0.018***	0.008***		0.003*
	(0.003)		(0.004)	(0.003)		(0.002)
Organising time						
Less than once a month			0.078***	0.020***		0.012***
			(0.007)	(0.004)		(0.003)
Less than once a week but at least once a month			0.079***	0.022***		0.011***
			(0.007)	(0.004)		(0.003)
At least once a week but not every day			0.081***	0.023***		0.013***
			(0.005)	(0.004)		(0.002)
Every day			0.082***	0.020***		0.009***
			(0.004)	(0.003)		(0.002)
Speeches / presentations						
Less than once a month	0.048***		0.031***	-0.003		-0.006***
	(0.003)		(0.003)	(0.002)		(0.002)
Less than once a week but at least once a month	0.051***		0.038***	-0.005*		-0.008***
	(0.004)		(0.004)	(0.003)		(0.002)
At least once a week but not every day	0.055***		0.037***	-0.004		-0.007***

	(0.004)		(0.005)	(0.003)		(0.002)
Every day	0.067***		0.020***	-0.012***		-0.010***
	(0.004)		(0.005)	(0.003)		(0.002)
Advanced mathematics / statistics						
Less than once a month		-0.002			-0.008**	
		(0.003)			(0.004)	
Less than once a week but at least once a month		0.006			-0.003	
		(0.005)			(0.005)	
At least once a week but not every day		0.006			-0.003	
		(0.005)			(0.005)	
Every day		0.007			-0.000	
		(0.005)			(0.005)	
Financial statements						
Less than once a month				0.003		
				(0.003)		
Less than once a week but at least once a month				0.005*		
				(0.003)		
At least once a week but not every day				0.009***		
				(0.003)		
Every day				0.012***		
				(0.002)		
Forms						
Less than once a month		0.050***	0.052***		0.066***	
		(0.003)	(0.004)		(0.003)	
Less than once a week but at least once a month		0.045***	0.051***		0.060***	
		(0.003)	(0.005)		(0.004)	
At least once a week but not every day		0.046***	0.053***		0.060***	
		(0.003)	(0.004)		(0.003)	
Every day		0.058***	0.064***		0.068***	
		(0.003)	(0.004)		(0.003)	
Task sequencing						
Less than once a month				0.052***		0.033***
				(0.003)		(0.002)
Less than once a week but at least once a month				0.049***		0.029***
				(0.003)		(0.002)
At least once a week but not every day				0.040***		0.025***
				(0.003)		(0.002)
Every day				0.039***		0.025***
				(0.003)		(0.002)
Supervision						
No			0.073***	0.037***		
			(0.002)	(0.002)		
Manuals						
Less than once a month		0.065***	0.060***		0.082***	
		(0.003)	(0.004)		(0.003)	
Less than once a week but at least once a month		0.060***	0.056***		0.075***	
		(0.003)	(0.004)		(0.003)	

At least once a week but not every day		0.062***	0.057***		0.077***	
		(0.003)	(0.004)		(0.003)	
Every day		0.059***	0.049***		0.075***	
		(0.003)	(0.004)		(0.003)	
Prices / budgets						
Less than once a month		0.005		-0.014***		-0.007***
		(0.003)		(0.003)		(0.002)
Less than once a week but at least once a month		0.006*		-0.012***		-0.004*
		(0.003)		(0.003)		(0.002)
At least once a week but not every day		0.008***		-0.014***		-0.002
		(0.003)		(0.003)		(0.002)
Every day		-0.001		-0.013***		0.000
		(0.002)		(0.002)		(0.001)
Professional texts						
Less than once a month		0.001				
		(0.003)				
Less than once a week but at least once a month		-0.001				
		(0.003)				
At least once a week but not every day		-0.004				
		(0.003)				
Every day		-0.005				
		(0.003)				
Programming						
Less than once a month		-0.006			-0.008	-0.004
		(0.005)			(0.005)	(0.003)
Less than once a week but at least once a month		0.006			0.000	-0.002
		(0.007)			(0.007)	(0.004)
At least once a week but not every day		0.010*			0.004	-0.001
		(0.006)			(0.006)	(0.004)
Every day		0.016***			0.012**	-0.007***
		(0.005)			(0.005)	(0.003)
Observations	7,102	7,099	7,090	7,089	7,100	7,085
R-squared	0.848	0.878	0.926	0.535	0.901	0.414

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on PIAAC and O*NET data.

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

VARIABLES	(25) Speech clarity	(26) Speech recognition	(27) Speed of closure	(28) Speed of limb movement	(29) Stamina	(30) Static strength
Email						
Less than once a month	0.150***	0.113***	0.013***	-0.012***	-0.020***	-0.027***
	(0.010)	(0.010)	(0.004)	(0.003)	(0.005)	(0.007)
Less than once a week but at least once a month	0.139***	0.128***	0.016***	-0.013***	-0.017***	-0.021***
	(0.011)	(0.011)	(0.004)	(0.004)	(0.005)	(0.007)
At least once a week but not every day	0.153***	0.111***	0.017***	-0.020***	-0.029***	-0.040***
	(0.007)	(0.007)	(0.002)	(0.002)	(0.003)	(0.005)
Every day	0.156***	0.114***	0.022***	-0.045***	-0.072***	-0.098***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)
Complex problems						
Less than once a month			0.037***	0.025***	0.040***	0.058***
			(0.002)	(0.002)	(0.002)	(0.003)
Less than once a week but at least once a month			0.036***	0.020***	0.030***	0.046***
			(0.002)	(0.002)	(0.003)	(0.004)
At least once a week but not every day			0.043***	0.020***	0.029***	0.047***
			(0.002)	(0.002)	(0.002)	(0.003)
Every day			0.045***	0.022***	0.033***	0.053***
			(0.002)	(0.002)	(0.003)	(0.004)
Planning						
Less than once a month	0.198***		0.009***	0.001	0.002	0.004
	(0.006)		(0.002)	(0.002)	(0.003)	(0.004)
Less than once a week but at least once a month	0.194***		0.005**	0.004*	0.004	0.007
	(0.006)		(0.003)	(0.002)	(0.003)	(0.005)
At least once a week but not every day	0.193***		0.005**	0.003	0.002	0.005
	(0.005)		(0.002)	(0.002)	(0.003)	(0.004)
Every day	0.192***		0.008***	0.001	-0.000	0.002
	(0.004)		(0.002)	(0.002)	(0.002)	(0.004)
Organising time						
Less than once a month			0.033***	0.020***	0.037***	0.048***
			(0.003)	(0.003)	(0.004)	(0.006)
Less than once a week but at least once a month			0.032***	0.015***	0.030***	0.038***
			(0.003)	(0.003)	(0.004)	(0.006)
At least once a week but not every day			0.035***	0.016***	0.029***	0.038***
			(0.002)	(0.002)	(0.003)	(0.005)
Every day			0.035***	0.013***	0.025***	0.033***
			(0.002)	(0.002)	(0.003)	(0.004)
Speeches / presentations						
Less than once a month	0.046***	0.048***	0.014***	-0.010***	-0.014***	-0.021***
	(0.004)	(0.004)	(0.002)	(0.001)	(0.002)	(0.003)
Less than once a week but at least once a month	0.047***	0.050***	0.015***	-0.011***	-0.016***	-0.025***
	(0.005)	(0.005)	(0.002)	(0.002)	(0.003)	(0.004)

At least once a week but not every day	0.053***	0.052***	0.015***	-0.011***	-0.015***	-0.024***
	(0.006)	(0.006)	(0.002)	(0.002)	(0.003)	(0.004)
Every day	0.114***	0.071***	0.005***	-0.012***	-0.014***	-0.024***
	(0.006)	(0.006)	(0.002)	(0.002)	(0.003)	(0.004)
Financial statements						
Less than once a month				-0.004**	-0.009***	-0.013***
				(0.002)	(0.003)	(0.004)
Less than once a week but at least once a month				-0.001	-0.004	-0.007*
				(0.002)	(0.003)	(0.004)
At least once a week but not every day				-0.001	-0.002	-0.004
				(0.002)	(0.002)	(0.003)
Every day				-0.002*	-0.007***	-0.012***
				(0.001)	(0.002)	(0.003)
Forms						
Less than once a month		0.223***	0.024***	0.005***	0.008***	0.012***
		(0.005)	(0.002)	(0.002)	(0.003)	(0.004)
Less than once a week but at least once a month		0.217***	0.022***	0.001	0.002	0.004
		(0.006)	(0.002)	(0.002)	(0.003)	(0.004)
At least once a week but not every day		0.217***	0.023***	0.004**	0.006**	0.010***
		(0.005)	(0.002)	(0.002)	(0.003)	(0.004)
Every day		0.221***	0.028***	0.012***	0.018***	0.028***
		(0.004)	(0.002)	(0.001)	(0.002)	(0.003)
Task sequencing						
Less than once a month				0.043***	0.081***	0.104***
				(0.002)	(0.003)	(0.004)
Less than once a week but at least once a month				0.039***	0.075***	0.095***
				(0.002)	(0.002)	(0.003)
At least once a week but not every day				0.035***	0.068***	0.085***
				(0.002)	(0.003)	(0.004)
Every day				0.034***	0.065***	0.082***
				(0.002)	(0.003)	(0.004)
Supervision						
No			0.032***			
			(0.001)			
Manuals						
Less than once a month			0.028***			
			(0.002)			
Less than once a week but at least once a month			0.026***			
			(0.002)			
At least once a week but not every day			0.027***			
			(0.002)			
Every day			0.024***			
			(0.002)			
Observations	7,102	7,105	7,090	7,084	7,084	7,084
R-squared	0.845	0.844	0.925	0.556	0.651	0.628

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on PIAAC and O*NET data.

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

VARIABLES	(31) Timesharing	(32) Visual colour discrimination	(33) Visualization	(34) Written comprehension	(35) Written expression
Email					
Less than once a month	0.018***			0.160***	0.140***
	(0.004)			(0.011)	(0.010)
Less than once a week but at least once a month	0.020***			0.150***	0.132***
	(0.004)			(0.012)	(0.011)
At least once a week but not every day	0.013***			0.172***	0.153***
	(0.002)			(0.007)	(0.006)
Every day	0.002			0.200***	0.188***
	(0.002)			(0.004)	(0.004)
Complex problems					
Less than once a month	0.048***		0.081***		
	(0.002)		(0.003)		
Less than once a week but at least once a month	0.044***		0.081***		
	(0.002)		(0.003)		
At least once a week but not every day	0.044***		0.086***		
	(0.002)		(0.003)		
Every day	0.044***		0.090***		
	(0.002)		(0.003)		
Planning					
Less than once a month				0.199***	0.162***
				(0.006)	(0.006)
Less than once a week but at least once a month				0.194***	0.159***
				(0.007)	(0.006)
At least once a week but not every day				0.197***	0.165***
				(0.005)	(0.005)
Every day				0.199***	0.168***
				(0.004)	(0.003)
Speeches / presentations					
Less than once a month		0.001		0.060***	0.059***
		(0.002)		(0.005)	(0.004)
Less than once a week but at least once a month		-0.005**		0.060***	0.063***
		(0.002)		(0.006)	(0.005)
At least once a week but not every day		-0.007***		0.062***	0.066***
		(0.003)		(0.007)	(0.006)
Every day		-0.024***		0.099***	0.105***
		(0.002)		(0.006)	(0.006)
Advanced mathematics / statistics					
Less than once a month			0.012***		
			(0.003)		
Less than once a week but at least once a month			0.022***		
			(0.005)		
At least once a week but not every day			0.021***		
			(0.005)		
Every day			0.027***		
			(0.005)		
Financial statements					

Less than once a month		0.000	0.006*
		(0.002)	(0.003)
Less than once a week but at least once a month		0.004*	0.012***
		(0.002)	(0.003)
At least once a week but not every day		0.005**	0.005*
		(0.002)	(0.003)
Every day		-0.004*	-0.004
		(0.002)	(0.003)
Sustained physical work			
Less than once a month		0.031***	0.047***
		(0.002)	(0.003)
Less than once a week but at least once a month		0.047***	0.059***
		(0.003)	(0.004)
At least once a week but not every day		0.053***	0.062***
		(0.002)	(0.003)
Every day		0.069***	0.086***
		(0.002)	(0.002)
Newspapers			
Less than once a month	0.010***	0.013***	
	(0.002)	(0.002)	
Less than once a week but at least once a month	0.010***	0.006**	
	(0.002)	(0.003)	
At least once a week but not every day	0.009***	0.003	
	(0.002)	(0.002)	
Every day	0.010***	0.005*	
	(0.002)	(0.002)	
Forms			
Less than once a month	0.022***		
	(0.002)		
Less than once a week but at least once a month	0.022***		
	(0.002)		
At least once a week but not every day	0.024***		
	(0.002)		
Every day	0.028***		
	(0.002)		
Task sequencing			
Less than once a month		0.069***	
		(0.002)	
Less than once a week but at least once a month		0.069***	
		(0.002)	
At least once a week but not every day		0.072***	
		(0.002)	
Every day		0.076***	
		(0.002)	
Supervision			
No	0.051***		
	(0.001)		
Manuals			
Less than once a month	0.030***		0.057***
	(0.002)		(0.003)

Less than once a week but at least once a month	0.026***		0.053***		
	(0.002)		(0.003)		
At least once a week but not every day	0.027***		0.055***		
	(0.002)		(0.003)		
Every day	0.024***		0.055***		
	(0.002)		(0.003)		
Prices / budgets					
Less than once a month		-0.003	0.006*		
		(0.002)	(0.003)		
Less than once a week but at least once a month		-0.000	0.006*		
		(0.003)	(0.004)		
At least once a week but not every day		-0.003	0.004		
		(0.002)	(0.003)		
Every day		-0.010***	-0.008***		
		(0.002)	(0.002)		
Professional texts					
Less than once a month	-0.003	0.008***	0.009***		
	(0.002)	(0.002)	(0.003)		
Less than once a week but at least once a month	0.002	0.011***	0.010***		
	(0.002)	(0.002)	(0.003)		
At least once a week but not every day	0.005**	0.013***	0.009***		
	(0.002)	(0.002)	(0.003)		
Every day	0.001	0.012***	0.006*		
	(0.003)	(0.003)	(0.003)		
Programming					
Less than once a month			0.006		
			(0.005)		
Less than once a week but at least once a month			0.023***		
			(0.007)		
At least once a week but not every day			0.023***		
			(0.006)		
Every day			0.035***		
			(0.005)		
Teamwork					
Less than once a month	0.049***	0.039***			
	(0.002)	(0.002)			
Less than once a week but at least once a month	0.056***	0.042***			
	(0.002)	(0.002)			
At least once a week but not every day	0.063***	0.041***			
	(0.002)	(0.002)			
Every day	0.071***	0.045***			
	(0.001)	(0.002)			
Observations	7,099	7,090	7,093	7,102	7,102
R-squared	0.940	0.894	0.877	0.860	0.859

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on PIAAC and O*NET data.

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

VARIABLES	(1) Arm-hand steadiness	(2) Auditory attention	(3) Category flexibility	(4) Deductive reasoning	(5) Dynamic strength	(6) Extent flexibility
Physical: 3-4	0.0200***	0.00715***	-0.00738***	-0.0121***	0.0116***	0.0181***
	(0.00326)	(0.00168)	(0.00174)	(0.00292)	(0.00180)	(0.00283)
5-6	0.0402***	0.0125***	-0.00862***	-0.0205***	0.0221***	0.0339***
	(0.00412)	(0.00212)	(0.00219)	(0.00369)	(0.00227)	(0.00358)
7-8	0.0538***	0.0176***	-0.0187***	-0.0334***	0.0316***	0.0494***
	(0.00332)	(0.00171)	(0.00177)	(0.00297)	(0.00183)	(0.00288)
9-10	0.0725***	0.0232***	-0.0206***	-0.0380***	0.0399***	0.0629***
	(0.00243)	(0.00125)	(0.00129)	(0.00218)	(0.00134)	(0.00211)
Use email: No	0.0264***	0.00763***	-0.0211***	-0.0411***	0.0189***	0.0298***
	(0.00308)	(0.00158)	(0.00164)	(0.00276)	(0.00170)	(0.00267)
Use computer: No	0.0182***	0.00503***	-3.70e-05	-0.00109	0.0195***	0.0309***
	(0.00304)	(0.00156)	(0.00162)	(0.00272)	(0.00168)	(0.00264)
Presenting: No	0.0726***	0.113***	0.308***	0.409***	0.0164***	0.0149***
	(0.00491)	(0.00252)	(0.00261)	(0.00440)	(0.00271)	(0.00426)
Presenting reversed: No	0.0495***	0.105***	0.319***	0.434***	0.00612**	-0.00199
	(0.00462)	(0.00237)	(0.00246)	(0.00414)	(0.00255)	(0.00401)
Changing order: Very little	0.00472*	0.000158	-0.00249*	-0.00451*	0.000979	0.00261
	(0.00268)	(0.00138)	(0.00143)	(0.00240)	(0.00148)	(0.00233)
To some extent	0.00846***	0.00295**	-0.00446***	-0.00638***	0.00182	0.00331
	(0.00249)	(0.00128)	(0.00132)	(0.00223)	(0.00137)	(0.00216)
To high extent	0.00791**	0.00351**	-0.00495***	-0.00601**	0.000996	0.00197
	(0.00320)	(0.00164)	(0.00170)	(0.00286)	(0.00176)	(0.00277)
To very high extent	0.0146***	0.0116***	-0.00433**	-0.00729**	0.00574***	0.00650**
	(0.00366)	(0.00188)	(0.00195)	(0.00328)	(0.00202)	(0.00318)
Read news: No	0.0115***	0.00228*	-0.000757	-0.00384*	0.00385***	0.00752***
	(0.00243)	(0.00125)	(0.00129)	(0.00218)	(0.00134)	(0.00211)
Read professional: No	-0.000631	-0.000113	-0.0130***	-0.0248***	0.00371***	0.00627***
	(0.00242)	(0.00124)	(0.00129)	(0.00217)	(0.00133)	(0.00210)
Use spreadsheets: No	0.0264***	0.00837***	-0.00664***	-0.00768***	0.0112***	0.0173***
	(0.00246)	(0.00126)	(0.00131)	(0.00220)	(0.00136)	(0.00213)
Use programming: No	-0.00868***	-0.00155	-0.0121***	-0.0124***	0.00274*	0.00170
	(0.00299)	(0.00154)	(0.00159)	(0.00268)	(0.00165)	(0.00259)
Supervising: No	0.0163***	-0.000994	-0.00986***	-0.0248***	0.00907***	0.0173***
	(0.00216)	(0.00111)	(0.00115)	(0.00193)	(0.00119)	(0.00187)

Complex problems: Less than once a month	0.00503	0.00661***	0.00967***	0.0136***	0.00166	0.00283
	(0.00311)	(0.00160)	(0.00166)	(0.00279)	(0.00172)	(0.00270)
Less than once a week but at least once a month	0.00420	0.00818***	0.0125***	0.0171***	-0.00108	-0.000447
	(0.00320)	(0.00165)	(0.00170)	(0.00287)	(0.00177)	(0.00278)
A least once a week but not every day	0.00758**	0.0110***	0.0170***	0.0247***	-0.000404	0.00176
	(0.00308)	(0.00158)	(0.00164)	(0.00276)	(0.00170)	(0.00267)
Every day	0.0141***	0.0120***	0.0179***	0.0236***	0.00154	0.00470
	(0.00349)	(0.00179)	(0.00186)	(0.00312)	(0.00192)	(0.00303)
Fill forms: No	-0.00307	-0.00672***	-0.00133	-0.00608***	0.00471***	0.00745***
	(0.00209)	(0.00107)	(0.00111)	(0.00187)	(0.00115)	(0.00181)
Observations	7,085	7,085	7,085	7,085	7,085	7,085
R-squared	0.831	0.930	0.979	0.964	0.788	0.766

Notes: Standard errors in parentheses. See Table 1 for questions associated with task items. *** p<0.01, ** p<0.05, * p<0.1

Source: Own estimations based on STEP and O*NET data.

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

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	-0.00374*	-0.0126***	0.0119***	0.00638***	-0.0107***	-0.00690***
	(0.00195)	(0.00257)	(0.00184)	(0.00163)	(0.00303)	(0.00186)
5-6	7.34e-05	-0.0237***	0.0232***	0.0120***	-0.0169***	-0.00933***
	(0.00246)	(0.00324)	(0.00232)	(0.00206)	(0.00383)	(0.00235)
7-8	-0.00589***	-0.0344***	0.0346***	0.0168***	-0.0290***	-0.0192***
	(0.00198)	(0.00261)	(0.00187)	(0.00166)	(0.00309)	(0.00189)
9-10	-0.00612***	-0.0403***	0.0423***	0.0232***	-0.0329***	-0.0214***
	(0.00145)	(0.00191)	(0.00137)	(0.00121)	(0.00226)	(0.00139)
Use email: No	-0.0192***	-0.0290***	0.0196***	0.00634***	-0.0432***	-0.0232***
	(0.00184)	(0.00242)	(0.00173)	(0.00154)	(0.00287)	(0.00176)
Use computer: No	0.00494***	-0.00705***	0.0186***	0.00587***	-0.00125	-0.000694
	(0.00181)	(0.00239)	(0.00171)	(0.00152)	(0.00283)	(0.00173)
Presenting: No	0.240***	0.300***	0.0167***	0.0961***	0.376***	0.354***
	(0.00293)	(0.00386)	(0.00276)	(0.00245)	(0.00457)	(0.00280)
Presenting reversed: No	0.244***	0.328***	0.00648**	0.0890***	0.401***	0.365***
	(0.00276)	(0.00363)	(0.00260)	(0.00231)	(0.00430)	(0.00264)
Changing order: Very little	-0.00141	-0.00602***	0.00136	8.54e-05	-0.00233	-0.00301**

	(0.00160)	(0.00211)	(0.00151)	(0.00134)	(0.00249)	(0.00153)
To some extent	-0.00215	-0.00797***	0.00270*	0.00216*	-0.00288	-0.00495***
	(0.00148)	(0.00196)	(0.00140)	(0.00124)	(0.00231)	(0.00142)
To high extent	-0.00227	-0.00869***	0.00195	0.00259	-0.00238	-0.00547***
	(0.00190)	(0.00251)	(0.00180)	(0.00160)	(0.00297)	(0.00182)
To very high extent	0.00109	-0.0107***	0.00512**	0.00912***	-0.00448	-0.00534**
	(0.00218)	(0.00288)	(0.00206)	(0.00183)	(0.00340)	(0.00209)
Read news: No	0.00181	-0.00556***	0.00315**	0.00279**	-0.00332	-0.000583
	(0.00145)	(0.00191)	(0.00137)	(0.00121)	(0.00226)	(0.00139)
Read professional: No	-0.0128***	-0.0208***	0.00417***	-0.00281**	-0.0278***	-0.0135***
	(0.00144)	(0.00190)	(0.00136)	(0.00121)	(0.00225)	(0.00138)
Use spreadsheets: No	0.000159	-0.00805***	0.0140***	0.00919***	-0.00182	-0.00617***
	(0.00147)	(0.00193)	(0.00138)	(0.00123)	(0.00229)	(0.00140)
Use programming: No	-0.0148***	-0.0128***	0.00535***	-0.00442***	-0.00996***	-0.0195***
	(0.00178)	(0.00235)	(0.00168)	(0.00149)	(0.00278)	(0.00171)
Supervising: No	-0.00834***	-0.0231***	0.00796***	-0.000583	-0.0202***	-0.0143***
	(0.00129)	(0.00169)	(0.00121)	(0.00108)	(0.00200)	(0.00123)
Complex problems: Less than once a month	0.0111***	0.00938***	0.000542	0.00710***	0.0136***	0.00944***
	(0.00185)	(0.00245)	(0.00175)	(0.00155)	(0.00289)	(0.00177)
Less than once a week but at least once a month	0.0149***	0.0126***	-0.00246	0.00833***	0.0163***	0.0139***
	(0.00191)	(0.00252)	(0.00180)	(0.00160)	(0.00298)	(0.00183)
A least once a week but not every day	0.0203***	0.0195***	-0.00198	0.0119***	0.0242***	0.0193***
	(0.00183)	(0.00242)	(0.00173)	(0.00154)	(0.00286)	(0.00176)
Every day	0.0221***	0.0178***	-0.000658	0.0134***	0.0245***	0.0208***
	(0.00208)	(0.00274)	(0.00196)	(0.00174)	(0.00324)	(0.00199)
Fill forms: No	-0.00596***	0.00255	0.00355***	-0.00511***	-0.00753***	-0.00311***
	(0.00125)	(0.00164)	(0.00118)	(0.00104)	(0.00194)	(0.00119)
Observations	7,085	7,085	7,085	7,085	7,085	7,085
R-squared	0.960	0.944	0.798	0.912	0.956	0.981

Notes: Standard errors in parentheses. See Table 1 for questions associated with task items. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on STEP and O*NET data.

Table B9. 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	-0.0113***	-0.00529***	-0.00652***	-0.0105***	-0.0132***	-0.0145***
	(0.00255)	(0.00129)	(0.00162)	(0.00215)	(0.00270)	(0.00309)
5-6	-0.0171***	-0.0111***	-0.00798***	-0.0164***	-0.0229***	-0.0277***
	(0.00321)	(0.00164)	(0.00204)	(0.00271)	(0.00340)	(0.00390)
7-8	-0.0350***	-0.0148***	-0.0170***	-0.0302***	-0.0336***	-0.0383***
	(0.00259)	(0.00132)	(0.00164)	(0.00218)	(0.00274)	(0.00314)
9-10	-0.0398***	-0.0169***	-0.0184***	-0.0334***	-0.0395***	-0.0452***
	(0.00190)	(0.000964)	(0.00120)	(0.00160)	(0.00201)	(0.00230)
Use email: No	-0.0254***	-0.0157***	-0.0221***	-0.0185***	-0.0383***	-0.0415***
	(0.00240)	(0.00122)	(0.00153)	(0.00203)	(0.00255)	(0.00292)
Use computer: No	-0.00696***	-0.00717***	0.000491	-0.00767***	-0.0133***	-0.0175***
	(0.00237)	(0.00121)	(0.00151)	(0.00200)	(0.00251)	(0.00288)
Presenting: No	0.255***	0.176***	0.378***	0.242***	0.469***	0.462***
	(0.00383)	(0.00195)	(0.00243)	(0.00323)	(0.00406)	(0.00465)
Presenting reversed: No	0.268***	0.190***	0.382***	0.250***	0.494***	0.494***
	(0.00361)	(0.00183)	(0.00229)	(0.00304)	(0.00382)	(0.00438)
Changing order: Very little	-0.00513**	-0.000500	-0.000209	-0.00477***	-0.00113	-0.00131
	(0.00209)	(0.00106)	(0.00133)	(0.00176)	(0.00221)	(0.00254)
To some extent	-0.00882***	0.00115	-0.00145	-0.00786***	0.00132	0.00306
	(0.00194)	(0.000987)	(0.00123)	(0.00164)	(0.00205)	(0.00236)
To high extent	-0.00836***	0.00169	-0.00127	-0.00698***	0.00155	0.00384
	(0.00249)	(0.00127)	(0.00158)	(0.00210)	(0.00264)	(0.00303)
To very high extent	-0.00853***	0.000744	-0.00206	-0.00720***	-0.00279	-0.000286
	(0.00286)	(0.00145)	(0.00181)	(0.00241)	(0.00303)	(0.00347)
Read news: No	-0.000514	-0.00308***	0.00168	-0.000501	-0.00741***	-0.00980***
	(0.00190)	(0.000965)	(0.00120)	(0.00160)	(0.00201)	(0.00230)
Read professional: No	-0.00784***	-0.0104***	-0.0116***	-0.00466***	-0.0212***	-0.0233***
	(0.00189)	(0.000961)	(0.00120)	(0.00159)	(0.00200)	(0.00229)
Use spreadsheets: No	-0.0229***	-0.00149	-0.00517***	-0.0197***	-0.00154	-0.00174
	(0.00192)	(0.000976)	(0.00122)	(0.00162)	(0.00203)	(0.00233)
Use programming: No	-0.0217***	-0.000882	-0.00775***	-0.0148***	0.00313	0.00996***
	(0.00233)	(0.00119)	(0.00148)	(0.00197)	(0.00247)	(0.00283)
Supervising: No	-0.0242***	-0.00930***	-0.00135	-0.0224***	-0.0169***	-0.0179***
	(0.00168)	(0.000856)	(0.00107)	(0.00142)	(0.00178)	(0.00204)
Complex problems: Less	0.00924***	0.00599***	0.00969***	0.00675***	0.0103***	0.0102***

than once a month						
	(0.00243)	(0.00123)	(0.00154)	(0.00205)	(0.00257)	(0.00295)
Less than once a week but at least once a month	0.0165***	0.00735***	0.0140***	0.0134***	0.0105***	0.00995***
	(0.00250)	(0.00127)	(0.00159)	(0.00211)	(0.00265)	(0.00304)
A least once a week but not every day	0.0217***	0.0103***	0.0171***	0.0176***	0.0135***	0.0130***
	(0.00240)	(0.00122)	(0.00152)	(0.00203)	(0.00254)	(0.00292)
Every day	0.0194***	0.00820***	0.0182***	0.0151***	0.0105***	0.00726**
	(0.00272)	(0.00138)	(0.00173)	(0.00230)	(0.00288)	(0.00331)
Fill forms: No	-0.00501***	-0.00229***	-0.00700***	-0.00516***	-0.00902***	-0.0101***
	(0.00163)	(0.000830)	(0.00104)	(0.00138)	(0.00173)	(0.00198)
Observations	7,085	7,085	7,085	7,085	7,085	7,085
R-squared	0.909	0.966	0.989	0.931	0.979	0.972

Notes: Standard errors in parentheses. See Table 1 for questions associated with task items. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on STEP and O*NET data.

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

VARIABLES	(19) Originality	(20) Perceptual speed	(21) Problem sensitivity	(22) Response orientation	(23) Selective attention	(24) Spatial orientation
Physical: 3-4	-0.0110***	-9.04e-05	-0.00675**	0.0115***	-0.000906	0.00640***
	(0.00260)	(0.00184)	(0.00301)	(0.00245)	(0.00121)	(0.00176)
5-6	-0.0208***	0.00494**	-0.00970**	0.0216***	0.00116	0.0119***
	(0.00329)	(0.00232)	(0.00380)	(0.00310)	(0.00153)	(0.00222)
7-8	-0.0306***	0.00189	-0.0163***	0.0312***	-0.000707	0.0166***
	(0.00265)	(0.00187)	(0.00306)	(0.00249)	(0.00123)	(0.00179)
9-10	-0.0357***	0.00422***	-0.0168***	0.0393***	-0.000471	0.0198***
	(0.00194)	(0.00137)	(0.00224)	(0.00183)	(0.000901)	(0.00131)
Use email: No	-0.0262***	-0.00980***	-0.0358***	0.0152***	-0.00874***	0.00962***
	(0.00246)	(0.00174)	(0.00284)	(0.00232)	(0.00114)	(0.00166)
Use computer: No	-0.00827***	0.00705***	0.000510	0.0179***	-0.000326	0.0124***
	(0.00242)	(0.00171)	(0.00281)	(0.00228)	(0.00113)	(0.00164)
Presenting: No	0.285***	0.208***	0.401***	0.0151***	0.250***	0.0104***
	(0.00392)	(0.00277)	(0.00453)	(0.00369)	(0.00182)	(0.00264)
Presenting reversed: No	0.314***	0.203***	0.417***	0.00208	0.252***	0.00354
	(0.00368)	(0.00260)	(0.00426)	(0.00347)	(0.00171)	(0.00249)
Changing order: Very little	-0.00558***	-0.000552	-0.00372	0.000629	-0.000170	-0.000639
	(0.00214)	(0.00151)	(0.00247)	(0.00201)	(0.000994)	(0.00144)
To some extent	-0.00675***	-0.000798	-0.00403*	0.00307	0.00169*	0.000446
	(0.00198)	(0.00140)	(0.00230)	(0.00187)	(0.000923)	(0.00134)
To high extent	-0.00776***	-0.000287	-0.00310	0.00426*	0.00218*	0.00140
	(0.00255)	(0.00180)	(0.00295)	(0.00240)	(0.00118)	(0.00172)
To very high extent	-0.0105***	0.00549***	-0.00348	0.0151***	0.00587***	0.00862***
	(0.00292)	(0.00206)	(0.00338)	(0.00275)	(0.00136)	(0.00197)
Read news: No	-0.00558***	0.00353***	-0.00279	0.00340*	0.000537	0.00140
	(0.00194)	(0.00137)	(0.00224)	(0.00183)	(0.000902)	(0.00131)
Read professional: No	-0.0213***	-0.00640***	-0.0255***	0.000699	-0.00586***	0.00263**
	(0.00193)	(0.00136)	(0.00223)	(0.00182)	(0.000898)	(0.00130)
Use spreadsheets: No	-0.00593***	0.000380	0.00445**	0.0144***	0.00254***	0.00526***
	(0.00196)	(0.00139)	(0.00227)	(0.00185)	(0.000913)	(0.00132)
Use programming: No	-0.0126***	-0.0129***	-0.00935***	0.00105	-0.00667***	0.000533
	(0.00238)	(0.00168)	(0.00276)	(0.00225)	(0.00111)	(0.00161)
Supervising: No	-0.0234***	-0.00477***	-0.0268***	0.00700***	-0.00400***	0.00158
	(0.00172)	(0.00121)	(0.00199)	(0.00162)	(0.000800)	(0.00116)
Complex problems: Less	0.00828***	0.00908***	0.0125***	0.00623***	0.00638***	0.00309*

than once a month						
	(0.00248)	(0.00175)	(0.00287)	(0.00234)	(0.00115)	(0.00167)
Less than once a week but at least once a month	0.0110***	0.0132***	0.0142***	0.00558**	0.00911***	0.00387**
	(0.00255)	(0.00180)	(0.00296)	(0.00241)	(0.00119)	(0.00172)
A least once a week but not every day	0.0182***	0.0168***	0.0218***	0.00831***	0.0118***	0.00545***
	(0.00245)	(0.00173)	(0.00284)	(0.00231)	(0.00114)	(0.00166)
Every day	0.0159***	0.0191***	0.0233***	0.00911***	0.0129***	0.00425**
	(0.00278)	(0.00196)	(0.00322)	(0.00262)	(0.00129)	(0.00188)
Fill forms: No	0.00442***	-0.00848***	-0.0112***	-0.00535***	-0.00595***	-0.00164
	(0.00167)	(0.00118)	(0.00193)	(0.00157)	(0.000776)	(0.00113)
Observations	7,085	7,085	7,085	7,085	7,085	7,085
R-squared	0.937	0.957	0.963	0.639	0.987	0.512

Notes: Standard errors in parentheses. See Table 1 for questions associated with task items. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on STEP and O*NET data.

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

VARIABLES	(25) Speech clarity	(26) Speech recognition	(27) Speed of closure	(28) Speed of limb movement	(29) Stamina	(30) Static strength
Physical: 3-4	-0.00978***	-0.00948***	-0.00436***	0.00810***	0.0137***	0.0182***
	(0.00267)	(0.00191)	(0.00145)	(0.00146)	(0.00202)	(0.00295)
5-6	-0.0253***	-0.0210***	-0.00587***	0.0150***	0.0263***	0.0347***
	(0.00337)	(0.00242)	(0.00183)	(0.00184)	(0.00256)	(0.00373)
7-8	-0.0305***	-0.0269***	-0.00989***	0.0213***	0.0383***	0.0503***
	(0.00271)	(0.00195)	(0.00147)	(0.00149)	(0.00206)	(0.00300)
9-10	-0.0362***	-0.0324***	-0.0115***	0.0272***	0.0474***	0.0653***
	(0.00199)	(0.00142)	(0.00108)	(0.00109)	(0.00151)	(0.00220)
Use email: No	-0.0301***	-0.0225***	-0.0169***	0.0137***	0.0225***	0.0304***
	(0.00252)	(0.00181)	(0.00137)	(0.00138)	(0.00191)	(0.00279)
Use computer: No	-0.0160***	-0.0167***	-0.000237	0.0154***	0.0197***	0.0279***
	(0.00249)	(0.00178)	(0.00135)	(0.00136)	(0.00189)	(0.00275)
Presenting: No	0.357***	0.366***	0.187***	0.00384*	0.0179***	0.0184***
	(0.00402)	(0.00288)	(0.00218)	(0.00220)	(0.00305)	(0.00444)
Presenting reversed: No	0.387***	0.379***	0.193***	-0.00427**	0.00722**	0.00121
	(0.00378)	(0.00271)	(0.00205)	(0.00207)	(0.00287)	(0.00418)
Changing order: Very little	-0.00116	-0.00214	-0.00147	0.000738	0.00173	0.00193
	(0.00219)	(0.00157)	(0.00119)	(0.00120)	(0.00166)	(0.00243)
To some extent	0.00404**	-0.000882	-0.00169	0.00185*	0.00342**	0.00483**
	(0.00203)	(0.00146)	(0.00110)	(0.00111)	(0.00154)	(0.00225)
To high extent	0.00566**	0.000830	-0.000768	0.00200	0.00244	0.00430
	(0.00261)	(0.00187)	(0.00142)	(0.00143)	(0.00198)	(0.00289)
To very high extent	0.00313	-0.00241	-0.000437	0.00693***	0.00609***	0.0144***
	(0.00299)	(0.00215)	(0.00162)	(0.00164)	(0.00227)	(0.00331)
Read news: No	-0.00947***	-0.00632***	-5.82e-05	0.00244**	0.00359**	0.00514**
	(0.00199)	(0.00142)	(0.00108)	(0.00109)	(0.00151)	(0.00220)
Read professional: No	-0.0183***	-0.00982***	-0.0112***	0.00268**	0.00493***	0.00541**
	(0.00198)	(0.00142)	(0.00107)	(0.00108)	(0.00150)	(0.00219)
Use spreadsheets: No	-0.00160	-0.00379***	-0.00106	0.00800***	0.0147***	0.0204***
	(0.00201)	(0.00144)	(0.00109)	(0.00110)	(0.00153)	(0.00223)
Use programming: No	0.0195***	0.0132***	-0.00758***	0.00215	0.00607***	0.00596**
	(0.00244)	(0.00175)	(0.00132)	(0.00134)	(0.00185)	(0.00270)
Supervising: No	-0.0157***	-0.0177***	-0.0119***	0.00695***	0.00860***	0.0154***
	(0.00176)	(0.00126)	(0.000956)	(0.000965)	(0.00134)	(0.00195)
Complex problems: Less	0.00732***	0.00262	0.00693***	0.00234*	4.68e-05	0.00519*

than once a month						
	(0.00254)	(0.00182)	(0.00138)	(0.00139)	(0.00193)	(0.00281)
Less than once a week but at least once a month	0.00588**	0.00283	0.0103***	0.000930	-0.00380*	0.000460
	(0.00262)	(0.00188)	(0.00142)	(0.00143)	(0.00199)	(0.00290)
A least once a week but not every day	0.00723***	0.00282	0.0142***	0.00199	-0.00359*	0.00199
	(0.00252)	(0.00180)	(0.00136)	(0.00138)	(0.00191)	(0.00278)
Every day	0.00102	0.000711	0.0144***	0.00267*	-0.00166	0.00533*
	(0.00285)	(0.00204)	(0.00155)	(0.00156)	(0.00216)	(0.00316)
Fill forms: No	-0.00617***	-0.00821***	-0.00489***	0.00181*	0.00528***	0.00490***
	(0.00171)	(0.00123)	(0.000927)	(0.000936)	(0.00130)	(0.00189)
Observations	7,085	7,085	7,085	7,085	7,085	7,085
R-squared	0.967	0.982	0.960	0.699	0.800	0.773

Notes: Standard errors in parentheses. See Table 1 for questions associated with task items. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on STEP and O*NET data.

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

VARIABLES	(31) Timesharing	(32) Visual colour discrimination	(33) Visualization	(34) Written comprehension	(35) Written expression
Physical: 3-4	0.00221**	0.00791***	0.00430*	-0.0169***	-0.0174***
	(0.00107)	(0.00187)	(0.00242)	(0.00345)	(0.00366)
5-6	0.00284**	0.0191***	0.0121***	-0.0306***	-0.0345***
	(0.00136)	(0.00236)	(0.00306)	(0.00436)	(0.00462)
7-8	0.00455***	0.0220***	0.00980***	-0.0492***	-0.0516***
	(0.00109)	(0.00190)	(0.00246)	(0.00351)	(0.00372)
9-10	0.00625***	0.0275***	0.0165***	-0.0574***	-0.0613***
	(0.000799)	(0.00139)	(0.00180)	(0.00257)	(0.00272)
Use email: No	-0.00258**	0.00309*	-0.000893	-0.0527***	-0.0539***
	(0.00101)	(0.00176)	(0.00229)	(0.00326)	(0.00345)
Use computer: No	-0.00377***	0.00940***	0.0135***	-0.0114***	-0.0124***
	(0.001000)	(0.00174)	(0.00226)	(0.00321)	(0.00341)
Presenting: No	0.188***	0.137***	0.194***	0.436***	0.397***
	(0.00162)	(0.00281)	(0.00364)	(0.00519)	(0.00550)
Presenting reversed: No	0.189***	0.131***	0.194***	0.469***	0.436***
	(0.00152)	(0.00264)	(0.00343)	(0.00489)	(0.00518)
Changing order: Very little	-0.000789	0.000395	-0.00361*	-0.00310	-0.00446
	(0.000882)	(0.00153)	(0.00199)	(0.00283)	(0.00300)
To some extent	0.00194**	0.000759	-0.00456**	-0.00332	-0.00379
	(0.000818)	(0.00142)	(0.00185)	(0.00263)	(0.00279)
To high extent	0.00287***	-8.30e-05	-0.00628***	-0.00258	-0.00284
	(0.00105)	(0.00183)	(0.00237)	(0.00338)	(0.00358)
To very high extent	0.00433***	0.00344	0.000611	-0.00640*	-0.00661
	(0.00120)	(0.00210)	(0.00272)	(0.00387)	(0.00410)
Read news: No	-0.00126	0.00644***	0.00478***	-0.00699***	-0.00956***
	(0.000800)	(0.00139)	(0.00180)	(0.00257)	(0.00272)
Read professional: No	-0.00482***	-0.00598***	-0.00935***	-0.0273***	-0.0289***
	(0.000796)	(0.00139)	(0.00180)	(0.00256)	(0.00271)
Use spreadsheets: No	0.00637***	0.00919***	0.00352*	-0.0136***	-0.0133***
	(0.000809)	(0.00141)	(0.00183)	(0.00260)	(0.00276)
Use programming: No	0.00404***	-0.0115***	-0.0239***	-0.00310	0.00210
	(0.000983)	(0.00171)	(0.00222)	(0.00316)	(0.00335)
Supervising: No	-0.0102***	-0.00208*	-0.00427***	-0.0211***	-0.0269***
	(0.000709)	(0.00123)	(0.00160)	(0.00228)	(0.00242)
Complex problems: Less	0.00240**	0.00615***	0.0130***	0.0156***	0.0158***

than once a month					
	(0.00102)	(0.00178)	(0.00231)	(0.00329)	(0.00349)
Less than once a week but at least once a month	0.00252**	0.00802***	0.0184***	0.0192***	0.0179***
	(0.00105)	(0.00183)	(0.00238)	(0.00339)	(0.00359)
A least once a week but not every day	0.00352***	0.0123***	0.0261***	0.0241***	0.0230***
	(0.00101)	(0.00176)	(0.00228)	(0.00325)	(0.00345)
Every day	0.00253**	0.0147***	0.0295***	0.0205***	0.0178***
	(0.00115)	(0.00200)	(0.00259)	(0.00369)	(0.00391)
Fill forms: No	-0.00635***	-0.00177	0.00103	-0.00930***	-0.00867***
	(0.000688)	(0.00120)	(0.00155)	(0.00221)	(0.00234)
Observations	7,085	7,085	7,085	7,085	7,085
R-squared	0.983	0.931	0.926	0.956	0.938

Notes: Standard errors in parentheses. See Table 1 for questions associated with task items. *** p<0.01, ** p<0.05, * p<0.1
Source: Own estimations based on STEP and O*NET data.

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 results of occupation-level models used for out-of-sample predictions of AI exposure

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	0.120***	2.451***	0.252***	-2.663***	-0.211***	0.074	0.219***	-0.124
	(0.036)	(0.365)	(0.032)	(0.491)	(0.067)	(0.351)	(0.048)	(0.075)
log (GDP pc)^2		-0.107***		0.116***		0.003		
		(0.018)		(0.024)		(0.017)		
Time trend (2022-2023)	-0.096***	-0.013	-0.040	0.172***	0.270***	-0.071**	0.026	0.161***
	(0.025)	(0.024)	(0.032)	(0.046)	(0.051)	(0.031)	(0.044)	(0.055)
Human Capital Index	-0.653*				4.417***			
	(0.371)				(1.185)			
Compulsory education		0.030***						
		(0.005)						
Harmonised test scores	0.002***	0.002***	0.002***					
	(0.001)	(0.000)	(0.000)					
Learning Adjusted Years of Schooling					-0.182***			0.063**
					(0.070)			(0.028)
University enrolment						0.002**	0.004***	
						(0.001)	(0.001)	
Survival rate from age 15-60				2.378***				0.806
				(0.481)				(0.585)
Share of population aged 15-64	-0.015***		-0.017***			-0.021***	-0.024***	
	(0.003)		(0.003)			(0.004)	(0.006)	

Population share with electricity		-0.014***						
		(0.002)						
Internet use	0.007***					0.008***		
	(0.001)					(0.001)		
Technology Infrastructure				0.075**	0.142***			
				(0.034)	(0.041)			
Participation in GVC, backward (EORA), 2011-2015						-0.433***	-0.372***	-0.750***
						(0.084)	(0.125)	(0.166)
ICT imports				-0.009**	-0.015***		0.006	
				(0.004)	(0.004)		(0.004)	
Log exports		0.003	0.001				-0.002	-0.045***
		(0.007)	(0.008)				(0.012)	(0.017)
Foreign direct investments								-0.001
								(0.001)
ISCO FE x-1	-	-	-	-	-	-	-	-
ISCO FE x-2	0.185***	-0.285***	0.099***	-0.497***	0.567***	-0.028	0.021	-0.567***
	(0.025)	(0.030)	(0.035)	(0.046)	(0.054)	(0.034)	(0.037)	(0.070)
ISCO FE x-3	0.004	0.626***	1.063***	-0.381***	0.002	0.072**	0.045	-0.625***
	(0.025)	(0.030)	(0.035)	(0.046)	(0.054)	(0.034)	(0.037)	(0.070)
ISCO FE x-4	-0.136***	0.775***	0.532***	-0.613***	-0.463***	0.118***		-0.250***
	(0.025)	(0.030)	(0.035)	(0.046)	(0.054)	(0.034)		(0.070)
ISCO FE x-5		0.521***	0.570***			0.120***		-0.205***
		(0.030)	(0.035)			(0.034)		(0.070)
ISCO FE x-6		0.446***						-0.393***
		(0.030)						(0.070)
Constant	-1.224***	-13.879***	-2.840***	13.987***	0.434	-1.324	-2.104***	-0.026
	(0.289)	(1.706)	(0.249)	(2.389)	(0.513)	(1.783)	(0.486)	(0.475)
Observations	316	474	395	316	316	395	237	474
R-squared	0.763	0.856	0.813	0.482	0.608	0.647	0.499	0.257

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

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



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