

Drivers of skill use at work

Authors: Piotr Lewandowski, Karol Madoń

Reviewer: Terry Gregory

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Abstract

We examine the evolution of skill use at work, measured with routine task intensity and the social skills index, across 27 high-income countries using harmonised data from two cycles of the OECD PIAAC survey (2011–2023). We find a broad decline in routine task intensity and a substantial increase in social skills use, with changes driven largely by within-occupation task adjustments rather than shifts in occupational structure. Econometric analysis shows that the growing computer use is the strongest correlate of de-routinisation, while associations with novel digital technologies are more heterogeneous. Exposure to Digital Infrastructure is associated with lower routine intensity, whereas Transactions technologies are associated with higher routine task intensity and lower social skills index. Higher human capital consistently predicts lower RTI and higher social skills index. We also document a persistent, though narrowing, gender gap in RTI, with women continuing to perform more routine-intensive tasks than men. Overall, the results show that changes in task content are uneven and depend on the function of particular technologies, the extent of ICT adoption, and the skill composition of the workforce.

Keywords: job tasks, occupations, technology, skills

JEL: J21, J23, J24, O33

1. Introduction

We investigate the evolution of skill use at work across 27 high-income countries between the early 2010s and the early 2020s to understand how digital technologies reshape the demand for skills. In particular, we focus on the routine content of work, measured by Routine Task Intensity (RTI), and on social-skill intensity, measured by the Social Skills Index (SSI). Our objective is to establish the associations between technological advancements, skill supply, and globalisation and the evolution of job content and skill use at work across developed countries.

Technological change affects both the demand for labour and the skills used at work. Early research showed that technological progress tends to increase demand for skilled relative to unskilled workers (Katz and Murphy, 1992). The task-based literature refined this view by showing that technology does not simply favour more educated workers, but tends to complement workers performing non-routine tasks while substituting for routine, codifiable activities (Acemoglu and Autor, 2011; Autor et al., 2003). As routine tasks become increasingly automated, social and interpersonal skills may become more valuable as complements to technology, particularly in jobs that require communication, coordination, and adaptability (Deming and Kahn, 2018; Deming, 2017). However, much of the task-based literature relies on occupational task measures derived from O*NET, which describe the task content of occupations in the United States. This is potentially restrictive because the same occupation can involve different tasks across countries. Existing evidence shows that occupational task content varies systematically with countries' level of development, technology use, skill supply, and participation in global trade (Caunedo et al., 2023; Lewandowski et al., 2022). Lewandowski et al. (2022) address this limitation by constructing country-specific measures of task content using PIAAC data, but their analysis is cross-sectional. We extend this approach by using country-specific, survey-based measures of RTI and social skill use to study how job content and skill use at work evolve within countries.

We quantify the changes in RTI and SSI using harmonised worker-level data from two cycles of the OECD Programme for the International Assessment of Adult Competencies (PIAAC), collected between 2011–2023 in 27 high-income countries. The PIAAC dataset allows constructing comparable task-based indicators and linking them to detailed measures of workers' education, literacy proficiency, and demographic characteristics. We complement these measures with sector-level indicators of exposure to emerging digital technologies, derived from an AI-driven mapping of patents to industries, as well as measures of participation in global value chains (GVC). This allows capturing the relationship between technology adoption and skill use at work, distinguishing between mature ICT (computers)

and emerging digital tools. This approach provides a comprehensive picture of how the task content of jobs is evolving and whether these changes differ across population groups, sectors, and countries.

Since the 1970s, ICT technologies have shaped the content of work, specifically reducing the demand for human labour in structured, routine tasks (Autor et al., 2003; Spitz-Oener, 2006) and increasing the role of social skills (Deming, 2017). We contribute to the literature by accounting for country-specific task content of jobs and distinguishing between various types of digital technologies. We also go beyond previous studies that established the relationship between technology adoption, skill supply, and global value chains and countries' task content of jobs and occupations (Caunedo et al., 2023; de la Rica et al., 2020; Lewandowski et al., 2022) by focusing on changes over time. In particular, we examine within-country changes in routine tasks and social-skill intensity and relate them to changes in technology use, skill supply, and globalisation. Our results show a broad decline in routine work across countries, driven mainly by changes in ICT intensity and within-occupation task adjustments rather than shifts in employment structure. However, different technologies are associated with different changes in task content: some are linked to lower routine intensity, while others are linked to higher routine intensity. Human capital remains a strong predictor of task content, and gender differences in RTI persist, although they narrow over time. These findings show that technological change reshapes job tasks unevenly, depending on the function of particular technologies and the skill composition of the workforce.

2. Data and measurement of tasks and skills

The worker-level dataset used in this study is derived from the OECD Programme for the International Assessment of Adult Competencies (PIAAC), a cross-country survey of adults conducted using a harmonised methodology that ensures comparability across participating countries. PIAAC provides information on respondents' basic skills, including literacy, numeracy, and problem-solving proficiency, as well as their occupation, sector of employment, and a comprehensive set of questions on tasks they perform at work. In this study, we focus on employed individuals aged 16–65. This allows us to account for cross-country differences in the task content of occupations while complementing standard human-capital characteristics, such as education and age, with direct measures of workers' skills. The data have a repeated cross-sectional structure with country samples typically comprising several thousand employed respondents. We use data from two PIAAC cycles covering 27 high-income countries. The

data were accessed through the OECD Remote Code Execution (RCE) service, as the scientific-use files for the second PIAAC cycle are not publicly available.

When selecting countries for the analysis, we restrict the sample to those participating in both cycles of the PIAAC survey. Several countries were excluded because they were covered in only a single cycle—for example, Switzerland, Croatia, Latvia, and Portugal—which prevents the construction of a harmonised two-cycle dataset. The final sample consists of the following countries: Austria, Belgium, Canada, Chile, the Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Hungary, Ireland, Israel, Italy, Japan, South Korea, Lithuania, the Netherlands, Norway, New Zealand, Poland, Sweden, Singapore, Slovakia, the United Kingdom, and the United States. For 21 out of 27 countries studied here, the first cycle PIAAC data were collected in 2011-2012 (Austria, Belgium, Canada, Czechia, Germany, Denmark, Estonia, Spain, Finland, France, Ireland, Italy, Japan, South Korea, the Netherlands, Norway, Poland, Sweden, Slovakia, the United Kingdom, and the United States), for five in 2014-2015 (Chile, Israel, Lithuania, New Zealand and Singapore), and for one in 2017-2018 (Hungary). The data for the second cycle of PIAAC were collected in 2022-2023.

We aim to measure the routine content of workers' jobs in a way that allows task content to differ both across countries and within occupations. We follow Lewandowski et al. (2022) and calculate a worker-level task measure of routine task intensity in the spirit of Acemoglu and Autor (2011). Using both PIAAC cycles allows us to study changes in routine task content over time within countries. We omit farmers and skilled agricultural workers (ISCO 6) from the sample. For methodological details, see Lewandowski et al. (2022). We calculate the worker-level routine task intensity according to the following formula:

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

where, r_{cog} , $nr_{analytical}$, $nr_{personal}$ are routine cognitive, non-routine cognitive analytical, and non-routine cognitive personal task levels. Unlike the O*NET-based RTI measure developed for the United States, our approach accounts for differences in task content both across countries and within occupations in each country. Particular task measures and RTI are standardised using their mean and standard deviation in the United States in 2011-2018 (PIAAC 1st cycle). Changes over time, as well as cross-country differences, can therefore be interpreted relative to the distribution of task content in the United States during the 2011-2018 survey (PIAAC 1st cycle).

Next, we create a worker-level measure of social skill use at work that is consistent with Deming (2017) measure of the social-skill intensity occupations based on the U.S. O*NET data, specifically as the average of four interpersonal abilities: social perceptiveness, coordination, negotiation, and persuasion.

Our objective is not to develop a new social skills index, but rather to extend an already existing, well-established measure to a cross-country setting and capture cross-country differences in the social skill use in seemingly identical occupations. To do so, we build on the approach of Lewandowski et al. (2025, 2022) and use individual-level information on work-related tasks from PIAAC.

Conceptually, we first use the 2011–2018 U.S. PIAAC sample (Cycle 1) to identify the survey questions that best approximate each of the four O*NET interpersonal abilities underlying Deming’s index. We estimate the relationships between PIAAC task measures and O*NET abilities in the United States and assess how closely the resulting PIAAC-based index reproduces the original measure. We then apply the estimated relationships to PIAAC data from other countries to construct a comparable worker-level social skills index. This approach preserves the conceptual framework of Deming (2017) while allowing the social skill intensity of the same occupation to vary across countries.

Because the O*NET components are defined at the occupation level, we first aggregate individual PIAAC responses to occupation-level averages. For each PIAAC question q , the occupation-level measure is defined as:

$$x_{jq} = \frac{1}{n_j} \sum_{i \in j} x_{iq}, \quad (2)$$

where x_{iq} denotes the response of worker i to question q , and n_j is the number of workers in occupation j . We then estimate a separate regression for each of the four O*NET social skill components:

$$S_{jk} = \beta_{0k} + \sum_{q \in Q_k} \beta_{qk} x_{jq} + \varepsilon_{jk}, \quad (3)$$

where S_{jk} denotes social skill component k for occupation j , and Q_k denotes the set of PIAAC questions used to approximate component k (social perceptiveness, coordination, negotiation, and persuasion). The questions entering each component are selected through an exhaustive search that maximises the correlation between predicted and observed O*NET values while keeping the specification parsimonious. Estimating the four components separately allows each to be approximated using its own set of PIAAC questions. See Table 1 for the list of PIAAC work-related questions we select to approximate the Social Skills Index (SSI) and Table A1 in the appendix for exact mapping between

questions and social skill components. See Table A2 in the appendix for the estimation of SSI components.

The predicted components are then combined using the same aggregation as in Deming (2017). The resulting PIAAC-based index closely reproduces the original O*NET measure in the U.S. calibration sample, with a correlation coefficient of 97.6%. This demonstrates that PIAAC work-related questions can closely approximate the established measure of social skills, providing a basis for extending it to other countries using country-specific information on task content.

Finally, we apply the coefficients estimated on the U.S. sample to occupation-level PIAAC task measures in each country covered in the study. For occupation j in country c , the predicted social skill component is:

$$\hat{S}_{jkc} = \hat{\beta}_{0k} + \sum_{q \in Q_k} \hat{\beta}_{qk} x_{jqc}, \quad (4)$$

and the country-specific Social Skills Index is:

$$SSI_{jc} = \frac{1}{4} \sum_{k=1}^4 \hat{S}_{jkc}. \quad (5)$$

The estimated coefficients are therefore held fixed across countries, while the underlying survey responses to PIAAC task measures are country-specific. The resulting index retains the definition of social skills derived from O*NET while allowing the task content of the same occupation to differ across countries. This approach allows us to account for cross-country differences in the task content of jobs and skill use at work rather than imposing the U.S. occupational task structure on all countries. The final SSI values are standardised with US mean and standard deviation.

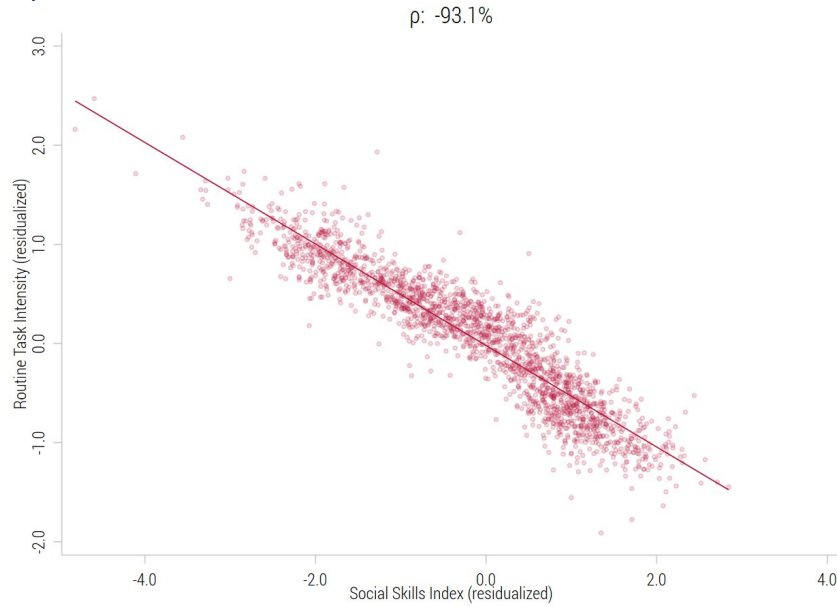
Table 1. PIAAC questions to calculate Routine Task Intensity and Social Skills Index		RTI	SSI
Q1	Are you allowed to change the sequence of your tasks?	X	X
Q2	And how often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution? The 30 minutes only refers to the time needed to THINK of a solution, not the time needed to carry it out.	X	X
Q3	How often does your job usually involve making speeches or giving presentations in front of five or more people?	X	X
Q4	In your job, what proportion of your time do you usually spend cooperating or collaborating with co-workers?	X	X
Q5	How often are you usually working physically for a long period?	X	
Q6	In your job, how often are you usually reading articles in newspapers, magazines or newsletters?	X	
Q7	In your job, how often are you usually, Read bills, invoices, bank statements or other financial statements?	X	
Q8	In your job, how often are you usually reading articles in professional journals or scholarly publications?	X	
Q9	In your job, how often are you usually filling in forms?	X	
Q10	In your job, how often are you usually reading manuals or reference materials?	X	
Q11	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?	X	
Q12	In your job, how often do you usually Use or calculate fractions, decimals or percentages?	X	
Q13	In your job, how often do you usually calculate prices, costs or budgets?	X	
Q14	In your job, how often are you usually using a programming language to program or write computer code?	X	
Q15	Do you manage or supervise other employees?		X
Q16	How often does your current job usually involve sharing work-related information with co-workers?		X
Q17	How often does your current job usually involve instructing, training or teaching people, individually or in groups?		X
Q18	How often does your current job usually involve selling a product or selling a service?		X
Q19	How often does your current job usually involve advising people?		X
Q20	How often does your current job usually involve planning your own activities?		X
Q21	How often does your current job usually involve organising your own time?		X
Q22	How often does your current job usually involve working to persuade or influence people?		X
Q23	How often does your current job usually involve negotiating with people either inside or outside your firm or organisation?		X
Q24	In your current job, how often do you usually write letters, memos or e-mails?		X
Q25	In your current job, how often do you usually use email?		X

Source: Own elaboration based on PIAAC data and Lewandowski et al. (2022).

We use Routine Task Intensity (RTI) and the Social Skills Index (SSI) as separate measures of task content. However, both indices describe how work is performed, raising the question of whether they capture distinct dimensions of work or largely reflect the same differences across occupations. In particular, we examine whether occupations characterised by greater routine intensity also tend to involve less social interaction.

To assess whether RTI and SSI are systematically related across occupations, we examine their association within countries and PIAAC cycles. To remove differences that are common to a given country in a given survey cycle, we regress each measure, at individual level, on a full set of country-by-cycle fixed effects, using employment weights based on ILO data. We then retain the residuals. Each residual shows how routine, or how social-skill-intensive, a worker's job is relative to the average worker in the same country and cycle. We then aggregate these residuals to ISCO 2-digit occupation $\times$ country $\times$ cycle cells. Each dot in Figure 1 therefore represents one ISCO 2-digit occupation in one country and one PIAAC cycle—for example, assemblers in Germany in 2011-2018 (PIAAC Cycle 1) and assemblers in Germany in 2022-2023 (PIAAC Cycle 2) appear as two separate observations. Comparing these adjusted occupation-level values isolates the relationship between RTI and SSI within countries, rather than differences driven by some countries being more technologically advanced, more service-oriented, or more highly skilled overall. Across the two PIAAC cycles, occupations became, on average, less routine-intensive and more social-skill-intensive (Figure 1). The two indices are strongly negatively correlated across occupations ($r \approx -0.93$, net of country-by-cycle effects), indicating that occupations characterised by greater routine intensity generally involve less social interaction. This relationship is consistent with the broader decline in RTI and increase in SSI observed between the two PIAAC cycles. Although the indices share four PIAAC task-use questions, most of their underlying questions are distinct. We therefore interpret them as complementary measures of task content, while recognising that the overlap may partly contribute to their strong negative correlation.

Figure 1. Relationship between (residualised) Routine Task Intensity and Social Skills Index within countries, by ISCO 2-digit occupations



Note: RTI and the SSI are residualised at the individual level using country-period fixed effects. Residuals are then averaged within ISCO 2-digit occupation × country × PIAAC-cycle cells. Each point therefore represents one occupation in one country and one PIAAC cycle.

Source: own elaboration based on PIAAC data.

3. Econometric approach

To examine the determinants of variation in RTI and SSI, we estimate OLS regressions of the form:

$$I_{ijsc} = \beta_0 + \beta_1 ICT_{sc} + \beta_2 NDT_s + \beta_3 H_{ijsc} + \tau_o + \beta_3 F_{sc} + \beta_4 D_c + \delta_c^{2022} + \varepsilon_{ijsc} \quad (6)$$

where, I_{ijsc} denotes the Routine Task Intensity or Social Skills Index of worker i in occupation j in sector s in country c , ICT_{sc} captures the ICT intensity in sector s in country c , NDT_s captures exposure to novel digital technologies in sector s , H_{ijsc} represents individual-level human capital, τ_o are occupation fixed effects, F_{sc} denotes firm characteristics in sector s in country c (including sector fixed effects), 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*).

We operationalise the key variables as follows:

- ICT intensity: share of workers using computers at the country–sector level, including a squared term to capture non-linear effects.
- Novel digital technologies: Digital Infrastructure, Transactions, Logistics, Automation and Monitoring Exposure indicators based on Prytkova et al. (2024).

- Human capital: worker-level indicators of educational attainment, test-based literacy proficiency (four levels), gender, and age (in 10-year groups).
- Occupational structure: controlled through 2-digit ISCO fixed effects.
- Firm characteristics: include the share of firms with websites, those using foreign-licensed technology, those holding internationally recognised quality certificates, and measures of forward and backward participation in global value chains (GVCs). All are defined at the country–sector level based on ISIC Rev.4, with 1-digit ISIC sector fixed effects.¹
- Development indicators: demeaned log GDP per capita (PPP) as a proxy for development level, interacted with country–sector fixed effects.

We allow the relationship between ICT intensity and task content to be non-linear by including both the share of workers using computers and its squared term. This follows Lewandowski et al. (2022), who document a non-linear relationship between country-sector computer use and RTI, with relatively small differences in RTI at low levels of computer use and a substantially stronger negative association at higher levels of ICT intensity.

To identify the digital technologies most likely to influence the evolution of job tasks, we build on the TechXposure framework of Prytkova et al. (2024) that tracks 40 emerging digital technologies and maps patent-based technological developments to industries. We use these technology-specific exposure measures as the starting point of our analysis and we aggregate them to five exposure groups: (1) Digital Infrastructure, combining Cloud Computing and Information Processing, whose sectoral exposure measures are correlated at 0.70; (2) Transactions, combining Online Shopping Platforms and Electronic Payments & Financial Transactions, also correlated at 0.70; (3) Logistics, combining Intelligent Logistics, Vehicle Telematics & Electric Vehicle Management, and Location-Based Services & Tracking, with pairwise correlations of around 0.60; (4) Automation Exposure, based on Industrial Automation & Robot Control; and (5) Monitoring Exposure, based on Remote Monitoring & Control Systems. Appendix B provides the details of our aggregation approach.

¹ 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.

Table 2. Adopted TechXposure description and grouping.

TechXposure	Technology description	Grouping
Cloud computing	Cloud computing and virtual machines, focusing on cloud platforms and resource allocation in cloud environments.	Digital Infrastructure
Information processing	Systems for managing, processing, and delivering data and information across various domains, potentially including content generation, transmission, and verification.	Digital Infrastructure
Online Shopping Platforms	Wireless technologies (e.g., RFID and mobile terminals), encryption (e.g., blockchain), and AI technologies for e-commerce transactions, and digital tools related to the purchase, sale, and display of product information, including recommendation systems.	Transactions
Electronic Payments & Financial Transactions	A combination of wireless (e.g., mobile) and encryption (e.g., blockchain) technologies for processing electronic payments (e.g., credit card transactions) and interfacing with financial institutions.	Transactions
Intelligent Logistics	A combination of monitoring, remote control technologies, data acquisition, and mobile robot technologies for logistics and delivery applications, including supply chain management, warehouse operations, package tracking, and courier services.	Logistics
Vehicle Telematics & Electric Vehicle Management	Technologies for intra-vehicle information management, especially in electric vehicles, including aspects of real-time monitoring, traffic information, and vehicle diagnostics.	Logistics
Location-Based Services & Tracking	Technologies that provide location-based content and services, often relying on global positioning and navigation systems and related communication technology.	Logistics
Industrial Automation & Robot Control	Industrial process automation, including robots, programmable logic controllers, and related control apparatuses such as remote control and fault diagnosis.	Automation Exposure
Remote Monitoring & Control Systems	Real-time remote monitoring and management technologies for factories, building management, warehouses, intelligent homes, disaster management, and network security.	Monitoring Exposure

Source: Adapted from Prytkova et al. (2024).

As a measure of globalisation, we utilise country-sector measures of participation in global value chains (GVCs). Globalisation increasingly involves the fragmentation of production across countries, with economies specialising not only in particular goods and stages of production but also in specific tasks (Grossman and Rossi-Hansberg, 2008). Such specialisation may therefore affect the task content of jobs and the relative importance of routine and non-routine work (Lewandowski et al., 2024). Our GVC measures come from the EORA database (Lenzen et al., 2012, 2013) and are computed following the methodology of Borin and Mancini (2019, 2015). In particular, we use both backward and forward GVC

participation measures. Both quantify value-added flows that cross at least two country borders. Backward GVC participation measures the share of imported inputs used in export production (% of total exports). Forward GVC participation captures the share of domestic value added embodied in a country's bilateral partners' exports (% of total exports).

We also control for firm-related indicators aggregated to the country-sector level to capture differences in firms' technological capabilities and propensity to adopt new technologies. These characteristics may be particularly relevant for the diffusion of emerging digital technologies, as sectors with more technologically advanced firms may be better positioned to adopt and integrate new tools into production. Specifically, we utilise the share of firms owning a website, using foreign-licensed technology, and holding an internationally recognised quality certificate, sourced from the World Bank Enterprise Surveys (WBES). To control for countries' development level, we use the natural logarithm of the GDP pc from the World Bank Development Indicators.

Because the regressions are cross-sectional over two periods, the results describe equilibrium distribution of routine-intensive tasks rather than causal effects. Nonetheless, ICT intensity, novel technologies and firm characteristics—defined at the aggregate country–sector or 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.

4. Results

4.1. Descriptive evidence

Between the early 2010s and early 2020s, jobs in high-income countries in our sample turned less routine-intensive and more social-skill-intensive. The average routine task intensity decreased by 0.15 US standard deviations across countries covered in both PIAAC cycles (Table 3). The decline is visible across all educational groups, with a strong negative gradient: the higher the education level, the weaker the decrease in RTI. However, these changes reflect large differences in initial RTI levels, as tertiary-educated workers were performing by far the least routine-intensive jobs. The comparison of raw means also indicates some convergence in RTI between men and women, as average RTI decreased slightly more among women. RTI also declined across all major occupational groups, except managers, for whom it remained broadly unchanged.

Social Skills Index increased on average by 0.77 US standard deviations in the countries studied. The increase was almost identical among men and women. In contrast to RTI, differences in changes across

education levels were less pronounced, although they followed a similar pattern. SSI also increased across all major occupational groups.

Table 3. Differences in average values of variables of interest between 1st PIAAC cycle (2011-2018) and 2nd PIAAC cycle (2022-2023)

	RTI		SSI		Digital Infrastructure	Transactions	Logistics	Automation exposure	Monitoring exposure
	Base level	Δ	Base level	Δ	Δ	Δ	Δ	Δ	Δ
Pooled sample	0.12	-0.15	-0.40	0.77	0.06	0.15	0.06	-0.06	0.03
Education: primary	0.77	-0.10	-1.30	0.76	-0.07	0.09	0.15	-0.11	0.03
Education: secondary	0.33	-0.07	-0.68	0.71	0.03	0.17	0.15	-0.03	0.08
Education: tertiary	-0.43	-0.04	0.33	0.62	0.12	0.15	-0.04	-0.08	-0.03
Men	0.04	-0.12	-0.47	0.78	0.20	0.17	0.19	0.16	0.30
Women	0.20	-0.17	-0.33	0.79	-0.09	0.13	-0.08	-0.31	-0.28
ISCO: 1	-0.81	0.01	1.27	0.43	0.20	0.31	0.15	-0.02	0.09
ISCO: 2	-0.60	-0.05	0.66	0.63	0.15	0.11	-0.11	-0.07	-0.06
ISCO: 3	-0.21	-0.06	0.35	0.61	0.09	0.10	-0.03	-0.06	0.02
ISCO: 4	0.31	-0.14	-0.31	0.70	0.18	0.35	0.17	-0.08	-0.02
ISCO: 5	0.46	-0.07	-0.76	0.71	-0.09	0.47	0.21	-0.40	-0.29
ISCO: 7	0.46	-0.15	-1.19	0.89	0.13	-0.17	0.04	0.58	0.84
ISCO: 8	0.87	-0.12	-2.03	0.93	-0.16	-0.11	0.31	0.01	0.05
ISCO: 9	1.09	-0.13	-2.51	0.90	-0.11	0.01	0.10	-0.23	-0.09

Note: variables of interest in columns: Routine Task Intensity (RTI), Social Skills Index (SSI); and exposures to novel technologies: Digital Infrastructure, Transactions, Logistics, Automation and Monitoring exposures. Values for novel technologies in PIAAC 1st cycle (2011-2018) are set to 0 and therefore are not reported. All Δs are the difference between the sample average in PIAAC 2nd and PIAAC 1st cycles, by groups (rows).

Source: own elaboration based on PIAAC data.

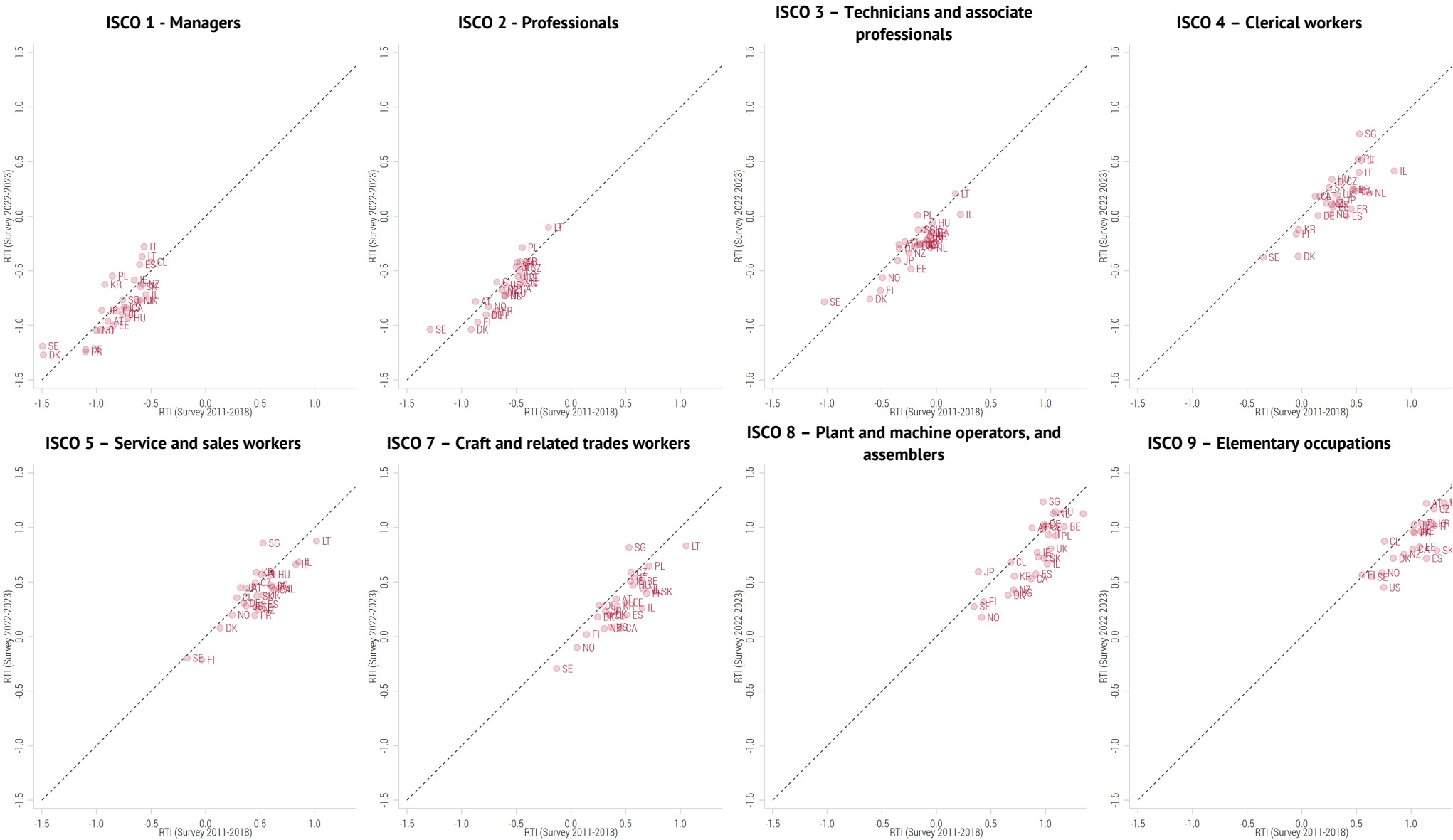
Next, we investigate changes in routine task intensity and social skill use across countries and occupational groups. Each subpanel of Figure 2 depicts the average RTI in 2011–2018 (PIAAC Cycle 1, x-axis) and 2022–2023 (PIAAC Cycle 2, y-axis), and a country-specific occupational marker below the 45-degree line indicates a decline in average RTI within that occupational group over time. Across countries, RTI generally declined between the two PIAAC cycles, indicating a broad shift away from routine tasks. The decline is visible across the occupational structure but is particularly pronounced among lower-skilled occupations (ISCO 7–9), which tend to have relatively high initial RTI levels. Middle-skilled occupations (ISCO 4–5), especially clerical support workers (ISCO 4), also experienced a noticeable decline in average RTI. In contrast, changes among high-skilled occupations (ISCO 1–3) are

more heterogeneous. In several countries, including Chile, Poland, and Singapore, RTI increased in some high- and middle-skilled occupational groups.

Taken together, these results reveal two consistent patterns. First, we document a broad decline in routine intensity across 27 high-income countries using harmonised worker-level data and a country-specific RTI measure that allows task content to vary both across countries and within occupations. This extends earlier cross-country evidence on de-routinisation, which has often documented declining employment shares of routine-intensive occupations using fixed occupation-level task measures (Goos et al., 2014, 2009). Recent evidence for Germany likewise documents continued de-routinisation through changes in occupational employment structure (Arntz et al., 2026). Our results show that declines in routine task intensity are also widespread within occupations across countries, introducing a within-country time dimension to country-specific measures of task content. Evidence on changes in task content within occupations over time has so far been concentrated largely in single-country studies, particularly for Germany (Spitz-Oener, 2006). Second, substantial cross-country variation remains, with some economies showing stable or even rising RTI in higher-skilled jobs. These differences suggest that aggregate declines in routine task intensity reflect both changes in occupational structure and within-occupation adjustments in task composition.

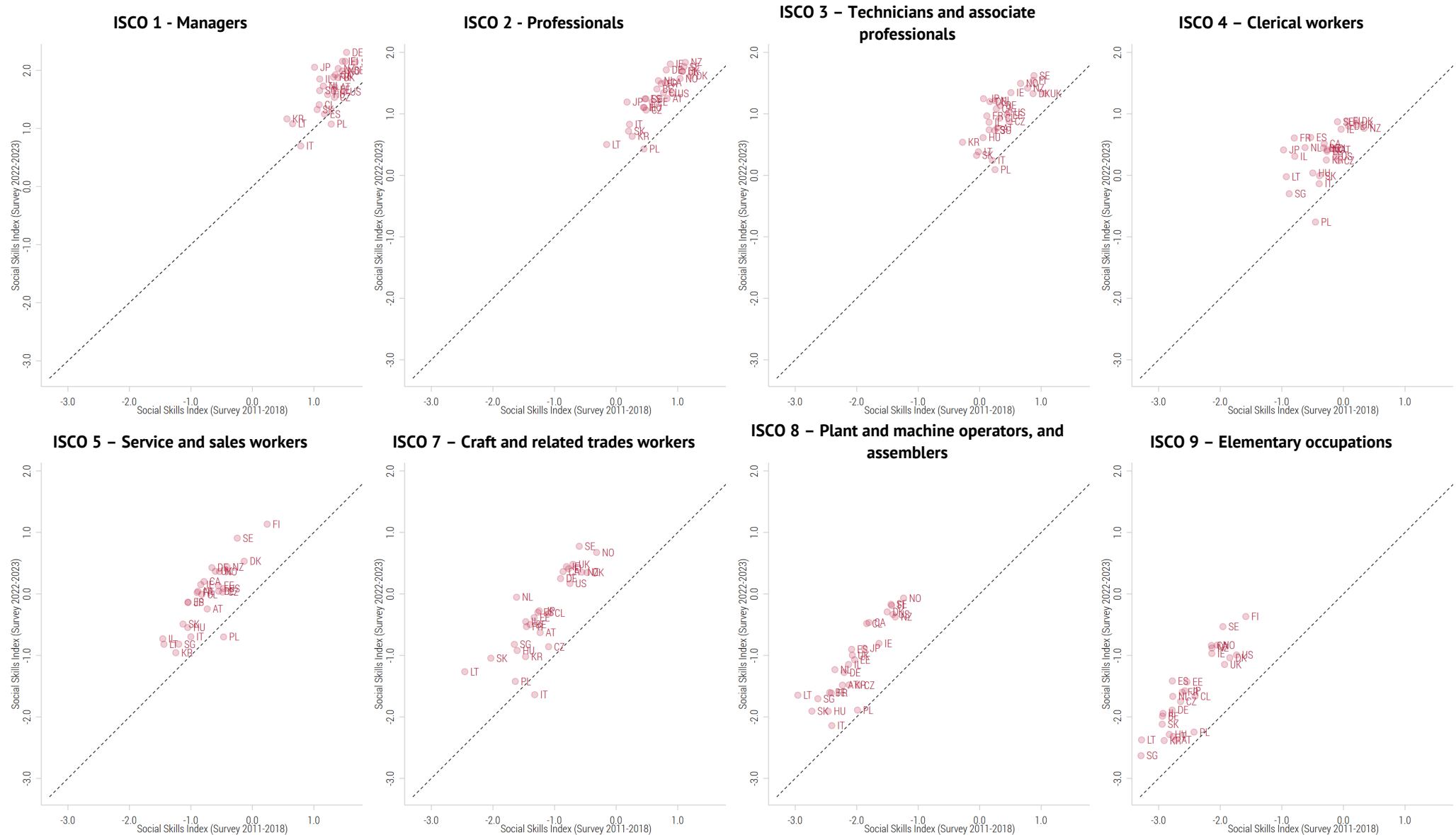
Similar patterns apply to social skills utilisation across occupational groups (Figure 3). The increase in SSI is visible across all ISCO 1-digit groups in almost every country (Figure 3). The largest increases occur in lower-skilled occupations (ISCO 7–9), followed by middle-skilled occupations (ISCO 4–5), while the smallest increases are observed among high-skilled occupations (ISCO 1–3), although they remain substantial. Poland stands out as a clear outlier, with SSI decreasing in several occupational groups, particularly among middle-skilled occupations.

Figure 2. Country-level average Routine Task Intensity (RTI) in 2011–2018 (PIAAC Cycle 1, X axis) and 2022–2023 (PIAAC Cycle 2, Y axis), by ISCO 1-digit occupational group



Note: The values of the RTI are standardised with the US mean and standard deviation. Source: Own calculations based on PIAAC data.

Figure 3. Country-level average Social Skills Index in 2011–2018 (PIAAC Cycle 1, X-axis) and 2022–2023 (PIAAC Cycle 2, Y-axis), by ISCO 1-digit occupational group



Note: The values of the Social Skills Index are standardised with the US mean and standard deviation. Source: Own calculations based on PIAAC data.

4.2. Econometric results

To identify key determinants of RTI and SSI, we estimate worker-level regressions based on Equation (7). Table 4 reports OLS results for the model without occupational fixed effects (columns 1 and 3), and with 2-digit ISCO fixed effects (columns 2 and 4). Including ISCO 2-digit fixed effects absorbs differences in average task content across occupations, so the remaining coefficients are identified from variation within narrowly defined occupations.

Access to digital technologies is strongly associated with routine task intensity. The positive and significant coefficient on computer use and the negative and significant coefficient on its squared term indicate an inverted U-shaped relationship between RTI and access to digital technologies. The relationship is present in the baseline specification and remains after controlling for ISCO two-digit occupation fixed effects. (Table 4, columns 1-2). In contrast, the model suggests a positive association between ICT intensity and the Social Skills Index, as only the squared term is positive and statistically significant (Table 4, columns 3-4).

We expect the associations between digital technologies and worker tasks to differ across technology types. Technologies related to automation or information processing may be associated with lower routine task intensity, whereas technologies related to transactions, monitoring, or logistics may be associated with higher routine task intensity through more standardised and codified work processes.

Our results show that the associations differ substantially across technology types. Digital Infrastructure exposure is consistently negatively associated with individual RTI, suggesting that workers employed in sectors more intensively exposed to cloud computing and information-processing technologies tend to perform fewer routine tasks (Table 4, columns 1-2). This is consistent with the idea that these technologies automate codifiable activities and complement non-routine analytical or interactive work. In contrast, Transactions technologies show a positive and significant association with RTI across all specifications (Table 4, columns 1-2). This implies that individuals working in sectors exposed to online shopping, e-payments, or other transactional platforms tend to engage in more routine tasks—possibly because these technologies standardise and formalise workflows, reinforcing routine processing and administrative tasks rather than replacing them. Logistics, automation and monitoring technologies show no meaningful relationship with individual RTI, suggesting these technologies do not translate into changes in the routine task profiles of workers outside the directly automated production segments.

In contrast, higher exposure to digital infrastructure is associated with a higher Social Skills Index in the specification without occupation fixed effects (Table 4, column 3). However, the association

disappears once ISCO 2-digit occupation fixed effects are included (column 4), suggesting that it is primarily driven by differences between occupations. This is consistent with digital infrastructure being more prevalent in occupations characterised by higher communication and social-skill intensity.

Transaction technologies are negatively associated with SSI in both specifications (Table 4, columns 3–4). Monitoring technologies are also negatively associated with SSI in the specification without occupation fixed effects, but this relationship disappears once ISCO 2-digit fixed effects are included. These patterns may be consistent with technologies related to process standardisation, compliance checking, and reporting being used in tasks that require less direct interpersonal interaction. Automation and logistics are not meaningfully correlated with SSI.

Human capital is a strong predictor of routine task intensity: higher education and literacy proficiency are both associated with significantly lower RTI (Table 4, columns 1–2). A worker at the highest literacy proficiency levels (4–5) has, on average, an RTI score 0.14 points lower than a comparable worker at level 2, conditional on ISCO two-digit occupation. More skilled individuals therefore tend to perform less routine-intensive tasks even within narrowly defined occupations. The skill-related coefficients weaken considerably once occupational controls are included, indicating that part of the association between human capital and RTI operates through occupational sorting. Women and, especially, younger workers also perform more routine-intensive jobs than men and prime-aged workers within similar occupations.

The opposite pattern emerges for the Social Skills Index. Higher education and literacy proficiency are associated with higher SSI, although these relationships weaken substantially once occupational fixed effects are included. This suggests that differences in SSI are partly related to occupational sorting but also persist within occupations for some dimensions of human capital. Gender and age are much weaker predictors of SSI. The youngest workers tend to be employed in less socially intensive occupations in the specification without occupational controls, but this difference disappears once ISCO two-digit fixed effects are included.

Firm and sector characteristics linked to globalisation are also associated with the Social Skills Index. At the sample mean of log GDP per capita, greater backward participation in global value chains (GVCs), measured as imported value added embodied in a country's exports (Borin and Mancini, 2019, 2015), is associated with lower SSI (Table 4, columns 3–4). In the specification without occupational fixed effects, the positive interaction with GDP per capita indicates that this negative association weakens in

higher-income countries, although the interaction loses statistical significance once ISCO two-digit occupational fixed effects are included. Forward GVC participation, measured as the share of domestic value added embodied in other countries' exports, is also negatively associated with SSI in both specifications. Among other firm characteristics, a higher prevalence of firms with websites is consistently associated with greater SSI.

In the case of RTI, backward GVC participation is not significantly associated with routine task intensity at the sample mean of GDP per capita. However, the positive interaction with GDP per capita in the specification with occupation fixed effects suggests that the association between backward GVC participation and RTI becomes more positive in high-income countries.

Overall, the results point to three main patterns. First, mature ICT use is strongly associated with task content, with a non-linear relationship for both RTI and SSI. Second, the associations of emerging digital technologies differ by function: Digital Infrastructure is associated with lower RTI, while Transactions are associated with higher RTI and lower SSI. Third, human capital remains strongly related to task content even within occupations, while the role of globalisation is more mixed and depends partly on countries' income levels.

Table 4. The correlates of individual RTI and SSI (OLS estimations)

	(1)	(2)	(3)	(4)
Variable	RTI	RTI	SSI	SSI
Computer use	0.774**	0.676*	-0.386	-0.511
	(0.388)	(0.384)	(0.641)	(0.603)
(Computer use) ²	-1.386***	-1.320***	1.903***	1.995***
	(0.297)	(0.291)	(0.466)	(0.437)
Novel digital technologies: Digital Infrastructure	-0.109***	-0.058***	0.113***	0.006
	(0.020)	(0.018)	(0.030)	(0.023)
Novel digital technologies: Transactions	0.028**	0.029**	-0.031*	-0.041**
	(0.012)	(0.012)	(0.018)	(0.017)
Novel digital technologies: Logistics	0.018	0.019	0.002	-0.007
	(0.016)	(0.015)	(0.018)	(0.017)
Novel digital technologies: Automation	-0.008	0.009	0.022	-0.003
	(0.017)	(0.016)	(0.021)	(0.018)
Novel digital technologies: Monitoring	0.025	-0.010	-0.065***	0.007
	(0.018)	(0.015)	(0.023)	(0.019)
Education: Primary	0.282***	0.154***	-0.357***	-0.005
	(0.014)	(0.012)	(0.020)	(0.011)
Education: Tertiary	-0.534***	-0.235***	0.696***	0.053***
	(0.012)	(0.010)	(0.018)	(0.006)
Low literacy proficiency (levels 1 or lower)	0.172***	0.083***	-0.271***	-0.036***
	(0.013)	(0.011)	(0.013)	(0.006)
Medium literacy proficiency (level 3)	-0.165***	-0.088***	0.201***	0.023***
	(0.008)	(0.007)	(0.009)	(0.004)
High literacy proficiency (levels 4 and 5)	-0.279***	-0.141***	0.324***	0.041***
	(0.013)	(0.011)	(0.013)	(0.008)
Gender: Woman	0.223***	0.205***	0.005	-0.024***
	(0.009)	(0.009)	(0.011)	(0.004)
Age: 16-24	0.369***	0.278***	-0.174***	-0.002
	(0.016)	(0.014)	(0.019)	(0.010)
Age: 35-44	0.080***	0.056***	-0.045***	0.000
	(0.009)	(0.009)	(0.008)	(0.004)
Age: 45-54	0.019**	0.023***	-0.001	-0.012***
	(0.008)	(0.007)	(0.009)	(0.004)
Age: 55-65	0.084***	0.090***	0.021*	0.002

	(0.011)	(0.009)	(0.011)	(0.006)
Forward GVC participation (GVCF) exports share	-0.146	-0.018	-0.310**	-0.438***
	(0.091)	(0.092)	(0.147)	(0.133)
GVCF share (std.) * [Ln(GDP pc) – mean(Ln(GDP pc))]	-0.410*	-0.339	0.297	0.259
	(0.224)	(0.229)	(0.357)	(0.350)
Backward GVC participation (GVCB) exports share	-0.077	-0.156	-0.587***	-0.380***
	(0.095)	(0.095)	(0.174)	(0.134)
GVCB share (std.) * [Ln(GDP pc) – mean(Ln(GDP pc))]	0.157	0.448**	0.869***	0.183
	(0.175)	(0.210)	(0.315)	(0.348)
Share of firms with a website	-0.003***	-0.003***	0.010***	0.009***
	(0.000)	(0.001)	(0.001)	(0.001)
Share of firms using licensed foreign technology	0.002	0.001	0.000	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Share of firms with an international quality certificate	0.001	0.000	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(GDP per capita) – mean(Ln(GDP per capita))	0.041	0.084	-0.193	-0.247
	(0.078)	(0.086)	(0.128)	(0.164)
Time trend (between 2020s and 2010s)	0.031	0.017	0.385***	0.431***
	(0.021)	(0.022)	(0.030)	(0.031)
Occupation fixed effects	No	ISCO 2D	No	ISCO 2D
Observations	191 707	191 707	193 135	193 135

Note: All regressions contain sector fixed effects (at 1-digit ISIC Rev. 4 classification) and sector fixed effects interacted with GDP per capita. Base categories – Men, Secondary education, aged 25-34, Lower-medium literacy proficiency (level 2). The estimation sample excludes Chile, Japan and Norway due to a lack of firm-level indicators. Standard errors clustered at the country-sector-survey cycle level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Own estimates based on PIAAC, WB, EORA and Prytkova et al. (2024) data.

4.3. Decomposition of changes in routine task intensity and social skills index over time

Next, we use the estimated coefficients from columns 2 and 4 of Table 4 to quantify the contributions of each explanatory variable to the within-country change in RTI and SSI. In particular, to assess the relative contribution of each factor, we use coefficients estimated from equation (6) to predict average RTI (SSI) by country, $\bar{I}_c$, and apply the covariance-based decomposition proposed by Morduch and Sicular (2002). The contribution of a variable group, k , to the variance of I_c is calculated as:

$$\sigma_k = \frac{cov(\beta_k \bar{X}_c^k, \bar{I}_c)}{var(\bar{I}_c)} \quad (7)$$

The average change in RTI between 2011-2018 and 2022-2023 (PIAAC survey periods) is -0.15 across countries in our sample. According to our models, changes in ICT intensity make the largest average contribution to this decline, at -0.15, which is equal in magnitude to the observed average decline. Changes in actual ICT adoption, measured as the share of workers using computers at the country-sector level, contribute substantially more to changes in RTI than changes in exposure to novel digital technologies (Figure 4). This may reflect the fact that computer use is a mature and widely diffused technology whose adoption changed substantially across sectors and countries over the period considered. Changes in ICT intensity therefore emerge as the most important observed contributor to the decline in RTI. The ICT contribution to RTI changes is negative in every country and is particularly large in Belgium, Ireland, Estonia, Germany, France, and the Czech Republic. Changes in occupational structure contribute a further -0.05 on average, while changes in development level contribute 0.04, human capital -0.02 and time trend 0.02. The average contribution of exposure to novel technologies is close to zero.²

The average change in SSI between 2011-2018 and 2022-2023 PIAAC survey periods is 0.77 across countries in our sample. According to our model, the time trend makes the largest average contribution to this increase, at 0.43, suggesting a secular shift towards performing tasks that require social skills which cannot be attributed to the observable factors we control for (Figure 5). One possible mechanism is the diffusion of digital technologies not captured by our ICT intensity measure or by our measures of exposure to novel technologies, which can reduce communication costs and facilitate coordination, collaboration, and information exchange across workers and organisations. The time trend may also capture other common shifts in job design.

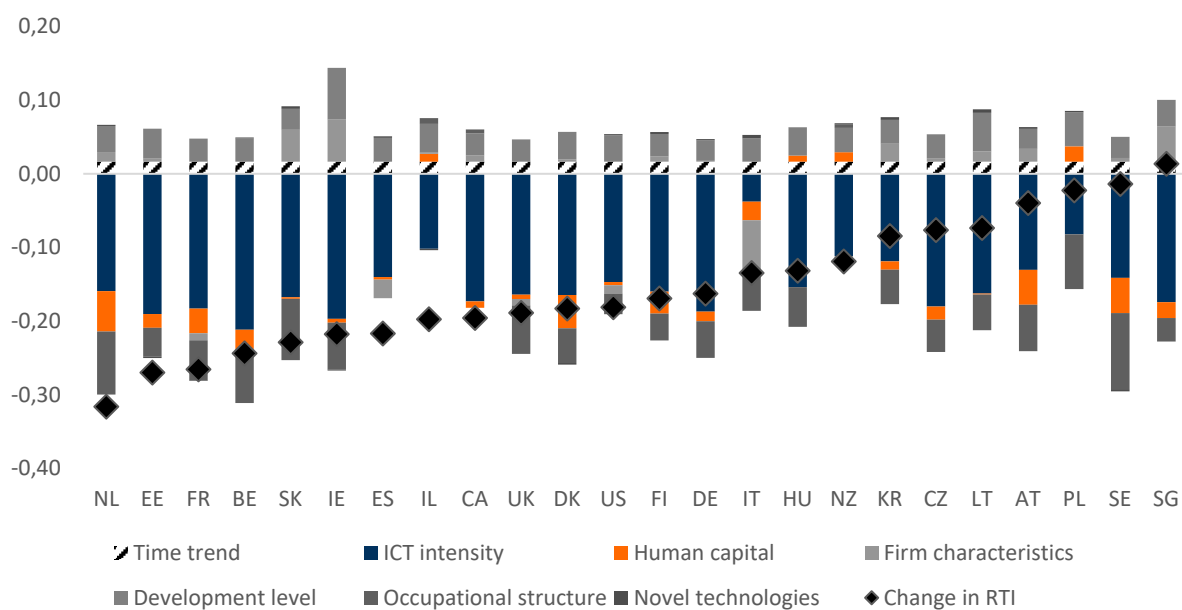
ICT intensity also contributes meaningfully to the SSI increase (0.29 on average). Changes in occupational structure contribute a further 0.09, while changes in development level contribute -0.04.

² Despite the aggregation of novel technology exposure into five broader dimensions, these measures remain relatively highly correlated (Appendix Table B1). This limits the precision with which the associations of individual technology groups can be distinguished. However, when considered jointly in the regression-based variance decomposition, novel technologies account for only around 1% of the explained cross-country variance. The remaining correlation therefore affects mainly the attribution across individual technology groups rather than the conclusion that their overall contribution is small.

The average contributions of human capital, firm characteristics and exposure to novel technologies are close to zero. Regarding the negligible contribution of exposure to novel digital technologies, many of these technologies are still at relatively early stages of diffusion, which may limit their contribution to changes in task content over the period covered by our data. Their role may become more important as adoption becomes more widespread.

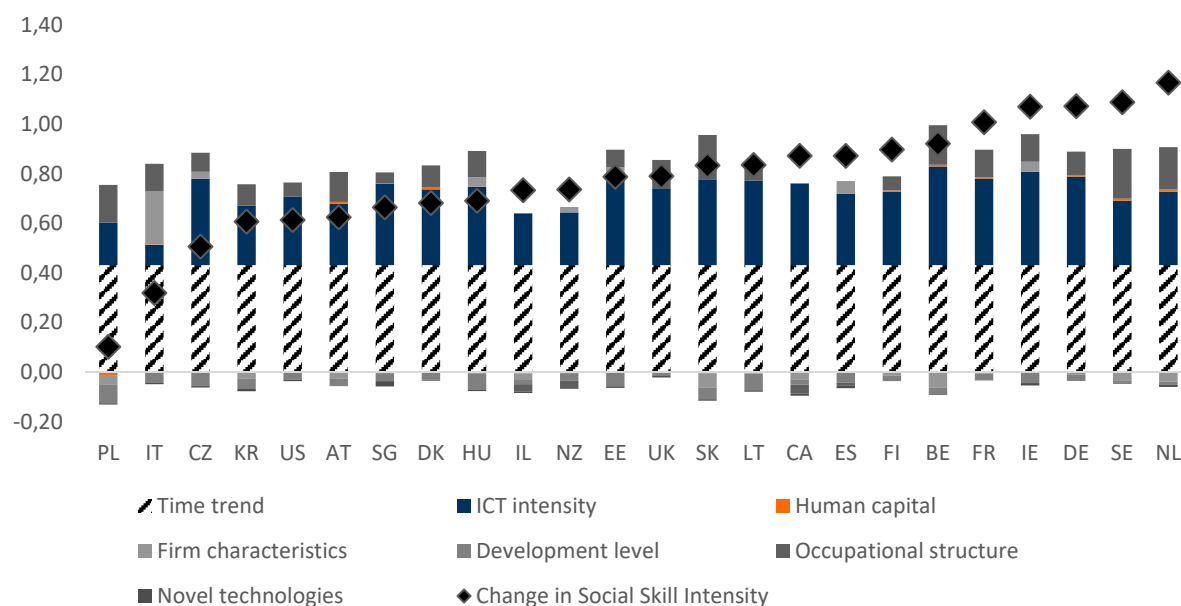
The relative importance of these components varies substantially across countries. The ICT contribution ranges from 0.08 in Italy to 0.40 in Belgium, while changes in occupational structure contribute particularly strongly in Sweden, Slovakia, the Netherlands, and Belgium. Poland is a notable exception: despite positive contributions from the time trend, ICT intensity, and occupational structure, the observed increase in SSI is only 0.10, indicating that a substantial part of the country-specific change remains unexplained by the decomposition.

Figure 4. Decomposition of the change in RTI into the estimated contributions of key factors, by country.



Source: own elaboration based on PIAAC, WB, and EORA data.

Figure 5. Decomposition of the change in SSI into the estimated contributions of key factors, by country.



Source: own elaboration based on PIAAC, WB, and EORA data.

5. Conclusions

The evolution of job tasks in high-income economies over the past decade confirms that digitalisation continues to reshape the nature of work, but not in uniform ways. Using harmonised microdata from two cycles of PIAAC, we provide systematic evidence on how routine task intensity (RTI) and the Social Skills Index have changed across 27 countries and identify the technological and human-capital factors behind these developments. Our results demonstrate a clear, cross-country decline in routine work, indicating a persistent shift away from codifiable and standardised activities and toward more complex, judgement-based tasks. At the same time, the Social Skills Index increased substantially. These changes, however, differ across countries, occupations, and demographic groups.

Three core conclusions emerge. First, de-routinisation remains primarily associated with established ICT use. Mature digital technologies—such as widespread computer utilisation—explain a significantly larger share of cross-country variation and change in RTI than emerging technologies. Changes in ICT intensity also account for a large part of the increase in the Social Skills Index. This suggests that economies are still absorbing productivity gains from past waves of digital adoption, and that these technologies continue to shape work more powerfully than newly diffusing tools.

Second, the estimated associations between novel digital technologies and task content differ across technology types. Greater exposure to Digital Infrastructure technologies is associated with lower RTI, while Transaction technologies are associated with higher RTI and lower Social Skills Index. Other

technology groups show weaker or less robust relationships. These results suggest that the relationship between digital technologies and task content depends on the functional characteristics of the technologies considered.

Third, human capital plays a central role in shaping the task content of jobs. Higher education and literacy proficiency are systematically related to lower RTI and higher Social Skills Index, although a substantial part of these differences operates through occupational sorting. Women and younger workers perform more routine-intensive tasks even within similar occupations, while changes over time indicate some narrowing of the gender gap in RTI. Nonetheless, significant differences remain, underscoring the need for targeted policies that align skill development with evolving task structures.

Overall, the findings suggest that digital transformation is associated with reconfiguration of task content rather than uniform decline in routine work. Policy responses should therefore prioritise strengthening foundational and transversal skills, supporting lifelong learning, and helping workers adapt to changing task requirements. The differing associations across emerging digital tools further emphasises the importance of policies that recognise the distinct pathways through which technologies influence job tasks. As technological diffusion progresses, adaptable skill systems may help respond more effectively to changing skill requirements.

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Appendix A – Social Skills Index

Table A1. The list of PIAAC questions used to proxy Social skills Index components

Coordination	Q1, Q2, Q4, Q18, Q20, Q22, Q23, Q24
Negotiation	Q1, Q2, Q15, Q16, Q17, Q21, Q22, Q25
Persuasion	Q1, Q2, Q3, Q15, Q16, Q21, Q22, Q25
Social perceptiveness	Q2, Q3, Q15, Q16, Q18, Q19, Q22, Q25

Source: own elaboration based on PIAAC data.

Table A2. Estimation of the PIAAC question weights for SSI components(OLS estimations)

	(1)	(2)	(3)	(4)
Variable	Coordination	Negotiation	Persuasion	Social perceptiveness
Q1 (task sequence)	0.750* (0.375)	0.571* (0.312)	0.625* (0.349)	
Q2 (complex problems)	0.668*** (0.236)	0.581*** (0.172)	0.879*** (0.201)	0.218 (0.194)
Q3 (presentations)			-0.342 (0.214)	-0.460 (0.293)
Q4 (cooperate)	0.746*** (0.134)			
Q15 (supervise)		-2.401*** (0.507)	-1.671*** (0.535)	-1.258** (0.604)
Q16 (share info)		-0.464*** (0.150)	-0.789*** (0.174)	-0.605** (0.251)
Q17 (teach)		-0.423** (0.160)		
Q18 (sell)	-0.317** (0.131)			-0.459*** (0.142)
Q19 (advise)				0.477* (0.268)
Q20 (plan activities)	0.415 (0.281)			
Q21 (organise time)		-0.535*** (0.183)	-0.553** (0.211)	
Q22 (influence)	0.303 (0.315)	1.001*** (0.127)	1.273*** (0.158)	1.360*** (0.214)
Q23 (negotiate)	1.137*** (0.347)			
Q24 (read letters)	-0.378** (0.150)			
Q25 (email)		0.375*** (0.092)	0.295*** (0.104)	0.339*** (0.100)
Constant	-6.382*** (0.924)	5.890*** (1.939)	4.058* (1.995)	2.028 (1.894)
N	39	39	39	39
R ²	0.921	0.951	0.942	0.922

Source: Own elaboration based on PIAAC data.

Appendix B – Novel technology measures

Technologies covered by Prytkova et al. (2024) differ substantially in scope. Some are relatively specific to applications or parts of the economy (e.g. 3D printing), while others capture broader technological developments (e.g. voice communication), and several are conceptually closely related (e.g. cloud storage & data security and cloud computing). We therefore apply an additional selection and aggregation procedure to retain the technologies most relevant for changes in worker tasks and to group related technologies into broader categories.

First, we rank the 40 technologies according to the number of patents assigned to each technology and retain those with above-median patent counts. This step is intended to exclude very niche technologies and focus on technologies that show a relatively high degree of technological development and diffusion. Second, we use several large language models to assess which of the remaining technologies are most likely to affect the tasks performed by workers. We compare the classifications produced by the different models and retain the technologies selected most consistently across them (see Table 2). Finally, because several of the selected technologies capture closely related technological functions, we aggregate them into broader conceptual groups. We first ask several large language models to propose groupings based on the functional similarity of the technologies. We then compare these classifications, assess pairwise correlations between sectoral exposure scores, and refine the grouping using expert judgement. High within-group correlations provide an additional indication that the technologies capture similar dimensions of sectoral exposure.

Table B1. The correlation matrix between composite novel technology measures

	Digital Infrastructure	Transactions	Logistics	Automation Exposure	Monitoring Exposure
Digital Infrastructure	1.00				
Transactions	0.74	1.00			
Logistics	0.75	0.67	1.00		
Automation Exposure	0.67	0.42	0.59	1.00	
Monitoring Exposure	0.68	0.42	0.60	0.87	1.00



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