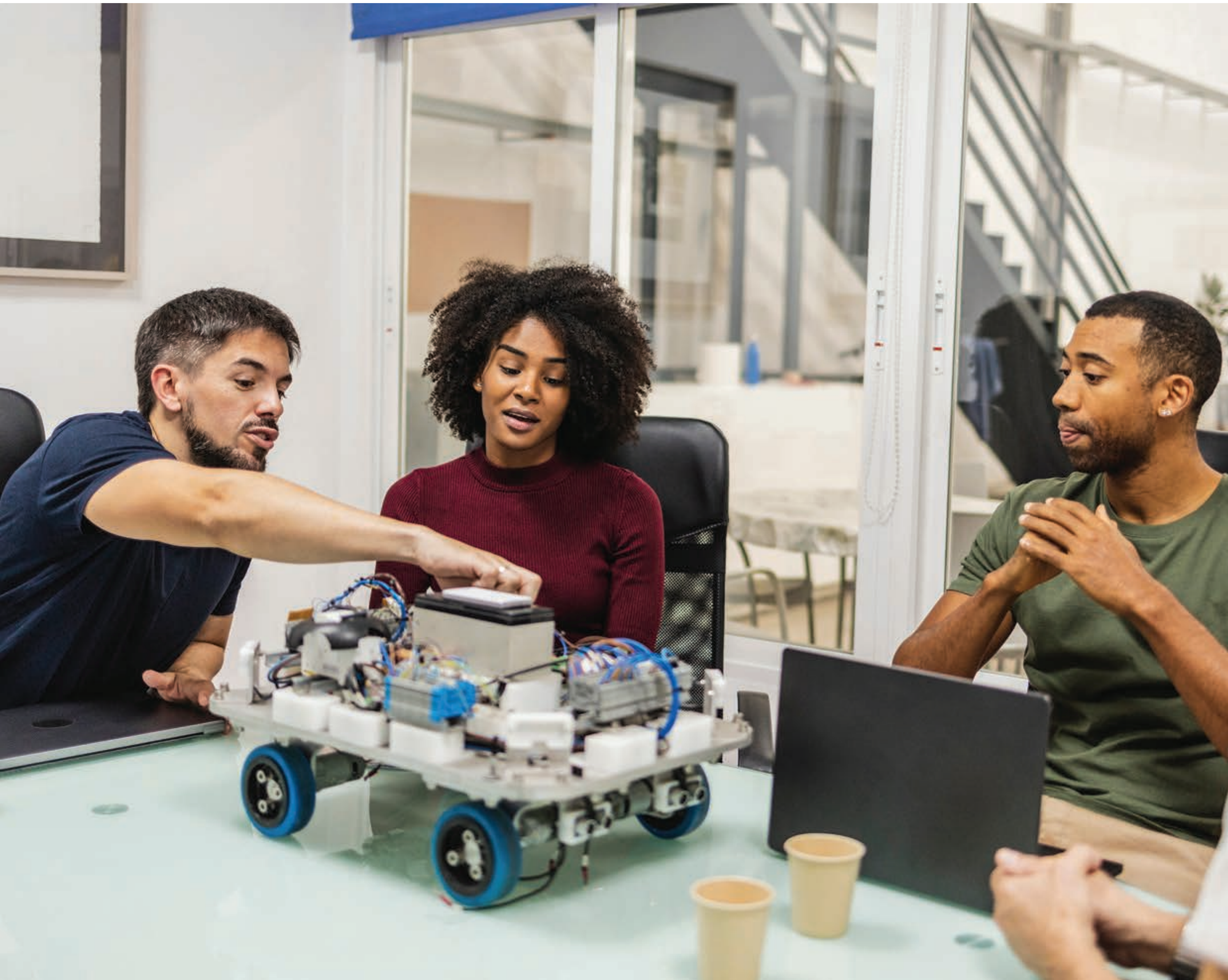
Getting Skills Right

How Workers Use, or Don't Use, their Skills in the Workplace



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How Workers Use, or Don’t Use, their Skills in the Workplace

OECD
BETTER POLICIES FOR BETTER LIVES

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Foreword

In recent decades, skills policies across OECD countries have focused primarily on expanding the supply of skills. Governments have made substantial investments in education, training and lifelong learning, improving access and attainment for millions of adults. These efforts have strengthened the foundation of human capital that underpins modern economies. However, developing skills is only part of the story. Evidence shows that economic and social returns depend not only on what people know, but also on how effectively their skills are put to use at work. In many countries, workers have limited opportunities to apply their skills on the job. This gap between potential and effective skills use represents a missed opportunity for individuals, firms and economies alike. When skills are not fully utilised, productivity and innovation suffer, job satisfaction declines and the benefits of training investments diminish.

This report draws on the latest cycle of the OECD Survey of Adult Skills to examine how the use of skills has evolved over the past decade and which skills are most frequently deployed in today's workplaces. It highlights cross-country patterns and differences, and analyses how skills use relates to wages, productivity and workers' well-being. The report also explores how individual and job characteristics – such as gender, educational attainment and occupation – shape skills use, identifying the groups and sectors where talent remains underutilised.

This PIAAC thematic report has been prepared as part of the work programme of the Board of Participating Countries (BPC) of the OECD Programme for the International Assessment of Adult Competencies (PIAAC). The BPC provides strategic oversight and guidance for the development and use of the Survey of Adult Skills. The Survey of Adult Skills assesses adults' proficiency in key information processing skills – literacy, numeracy and adaptive problem solving – and collects a wide range of information on how adults use their skills at work and in everyday life. By enabling cross-country comparisons and in-depth policy analysis, the survey helps countries to better understand how skills are developed, maintained and used over the life course.

The report was prepared by Michele Tuccio from the Directorate for Employment, Labour and Social Affairs, under the supervision of Glenda Quintini (Head of the Skills and Future Readiness Division). Valuable comments were received by Stefano Scarpetta (Directorate for Employment, Labour and Social Affairs), as well as Andreas Schleicher and Anja Meierkord (Directorate for Education and Skills). Feedback and comments on this report by members of the BPC are also gratefully acknowledged.

Table of contents

FIGURES

TABLES

Executive summary

A higher skilled workforce is widely recognised as crucial to achieve high productivity growth and competitiveness. Yet, much less attention is given to the demand side of the equation: how the skills developed in education and adult learning are actually deployed in the workplace. This question is important: even when workers acquire high levels of skills proficiency through education and training, their skills may remain underutilised on the job. Using data from the 2023 Survey of Adult Skills (PIAAC), this report finds evidence of a broken link between skills proficiency and skills use. Countries with higher average proficiency levels in literacy, numeracy or adaptive problem solving do not necessarily report more frequent use of these skills at work, and within each country, a large share of highly skilled workers use their skills only rarely. In countries such as Singapore and Croatia, this share reaches one in three workers.

Studying skills use is essential because the way skills are deployed in the workplace has important implications for both the economy and workers themselves. The analysis shows that greater use of skills is associated with higher labour productivity, with high-productive economies such as Ireland, Norway and the United States also displaying a more frequent use of skills. At the individual level, more frequent skills use is strongly linked to higher wages: for example, a one-standard-deviation increase in the use of influencing skills corresponds to a 7% rise in hourly wages, all else being equal. At the macro level, the report also finds that inequality in skills use mirrors wage inequality across countries, suggesting that unequal deployment of skills contributes to broader disparities in earnings.

The deployment of skills in the workplace is also correlated with non-economic outcomes. Workers who are able to use their skills more fully tend to report higher levels of job and life satisfaction, indicating that effective skills utilisation enhances motivation and engagement. The analysis also examines another dimension of job quality and worker well-being that has been so far overlooked in the economic research: the risk of job burnout. Burnout represents a critical outcome to consider as it reflects the potential costs of skills use when workers face persistent mismatches between their skills and the conditions under which they are deployed. Computing a composite index of burnout risk, this report finds that greater use autonomy and discretion at work is strongly associated with a lower risk of burnout.

Exploiting the most recent PIAAC data, the report shows that self-organisation and task discretion are the most widely used skills in nearly all countries surveyed, reflecting the growing importance of autonomy and responsibility in modern workplaces. Co-operative skills are also used frequently, consistent with evidence that social and interpersonal skills are becoming increasingly valuable in labour markets.

Drawing on the two cycles of the Survey of Adult Skills, the report also provides a unique perspective on how skills use has evolved over the past decade. ICT use has expanded more than any other skill domain. A decomposition analysis suggests that this increase is mostly due to more use of ICT skills within occupations, rather than shifts in occupational composition. By contrast, the use of dexterity skills has declined sharply in many countries, including France, the United Kingdom and Germany, reflecting the ongoing transformation of task structures within occupations.

Disparities in skills use remain significant. In 2023, women still use most skills at work less frequently than men with the same individual and job characteristics, including similar occupations and proficiency levels.

This likely reflects task segregation within occupations, where men and women are assigned different responsibilities. More concerningly, women's use of key information-processing skills at work – such as numeracy, reading, writing and ICT – has declined relative to men's over the past decade. Addressing these gaps requires workplace-level interventions to promote fair task allocation and inclusive management practices.

Low-qualified workers also use most skills less frequently than their more educated peers, even when they have the same proficiency level. Encouragingly, however, this gap has narrowed over time. In particular, low-qualified workers have increased their use of numeracy, ICT and influencing skills – which are central to adapting to more complex work environments – more than highly qualified workers. Decomposition results point at a process of job upgrading, with most of the observed catching-up effect explained by jobs themselves becoming more skill-intensive, rather than by low-qualified workers moving into new, more demanding occupations.

Overall, the findings of this report indicate that expanding the pool of highly skilled workers is necessary but not sufficient for productivity growth. Bridging the gap between skills proficiency and skills use is essential for ensuring that talent is fully utilised and that productivity gains are broadly shared. Persistent mismatches between workers' skills and how they are deployed suggest labour market inefficiencies, which can be simultaneously due to managerial practices that fail to leverage employee potential and workers taking jobs below their skill level due to labour market rigidities. Policy efforts should therefore encourage firm-level innovation and job redesign to make better use of existing skills. At the same time, governments should increase efforts in strengthening labour market institutions and career guidance systems to facilitate better skill matching.

1 Which skills are used where

A highly proficient workforce does not automatically lead to greater use of skills. Understanding the different patterns of skills use at work is essential to design effective measures to raise productivity and improve job matching. Drawing on data from the 2023 Survey of Adult Skills, this chapter examines the relationship between workers' proficiency levels and their actual use of skills at work. It highlights significant cross-country differences in the extent to which different skills are used in the workplace. The chapter also explores how skills use varies across different groups of workers and types of jobs, identifying patterns linked to factors such as gender, age, education, occupation and industry.

In Brief

High skills do not always lead to high-skill work

- Across OECD countries, there is a substantial pool of untapped talent: individuals with strong skills who are not given adequate opportunities to apply them in their daily work.
- The skills most commonly used in the labour market are self-organisation, task discretion, and co-operative skills, reflecting a growing premium on autonomy, collaboration, and adaptability. Workers increasingly rely on personal initiative and teamwork rather than on information-processing skills such as numeracy, reading, and writing, which are used less often.
- On average, women use their skills less often than men in the workplace, even when they have similar proficiency levels and hold comparable roles. This suggests that workplace task allocation may be biased by gender norms.
- Differences in skills use between age groups are not solely the result of ageing, but vary considerably with task type. Numeracy use typically peaks in mid-career before declining, learning-at-work skills decrease steadily with age, and self-organisation skills rise and then stabilise as workers gain experience and autonomy.
- Having a degree does not always translate into greater skills use, even after controlling for occupation. For example, graduates use numeracy, task discretion, and learning-at-work skills at similar levels to those with only upper secondary education. However, without at least upper secondary qualifications, access to skill-intensive work remains limited.
- Skills use varies systematically across occupations and industries. High-skilled roles such as managers and professionals rely heavily on cognitive and social skills, while lower-skilled and manual occupations depend more on physical and dexterity skills. Co-operation and self-organisation skills are widely used across all industries, underscoring the universal value of teamwork and autonomy, whereas ICT skills are concentrated in digitally intensive sectors like finance and communications.

Introduction

Across the OECD, skill policies have historically emphasised the supply side: investments in lifelong learning, training participation, and qualifications. This focus reflects the relative ease of targeting supply levers through public policy. Expanding access to adult learning, improving the quality of training, and increasing overall skills proficiency are all well-established goals. Yet, this emphasis has often come at the expense of serious attention to how skills are actually deployed in workplaces. A growing body of research suggests that improving the stock of human capital is only part of the equation; how employers use those skills – i.e. the demand side – is equally critical for translating capabilities into economic performance (Cappelli, 2015[1]; Russo, 2017[2]).

The distinction between skills supply and skills use has important implications. Even when workers acquire high levels of proficiency through education or training, their skills may not be used regularly or effectively on the job. This underutilisation of skills has received some attention shortly after the release of the first cycle of the OECD Survey of Adult Skills (PIAAC), which highlights a persistent gap between what people are capable of and what they actually do at work (Quintini, 2014[3]; OECD, 2016[4]; OECD, 2016[5]; Jonas, 2018[6]). Workers in many OECD countries report lower levels of engagement with problem solving, numeracy, and literacy tasks than would be expected given their actual skills proficiency. The result is a form of latent human capital: skills that exist but are not activated, thereby reducing the potential returns to investment in education and training.

This gap has both microeconomic and macroeconomic consequences. At the firm level, poor skills utilisation can constrain productivity, reduce innovation potential, and lead to suboptimal work organisation. At the individual level, it can dampen job satisfaction, limit career progression, and contribute to disengagement or turnover. At the national level, this translates into lower aggregate productivity growth, reduced competitiveness, and weaker returns on public and private investments in education and training.[1]

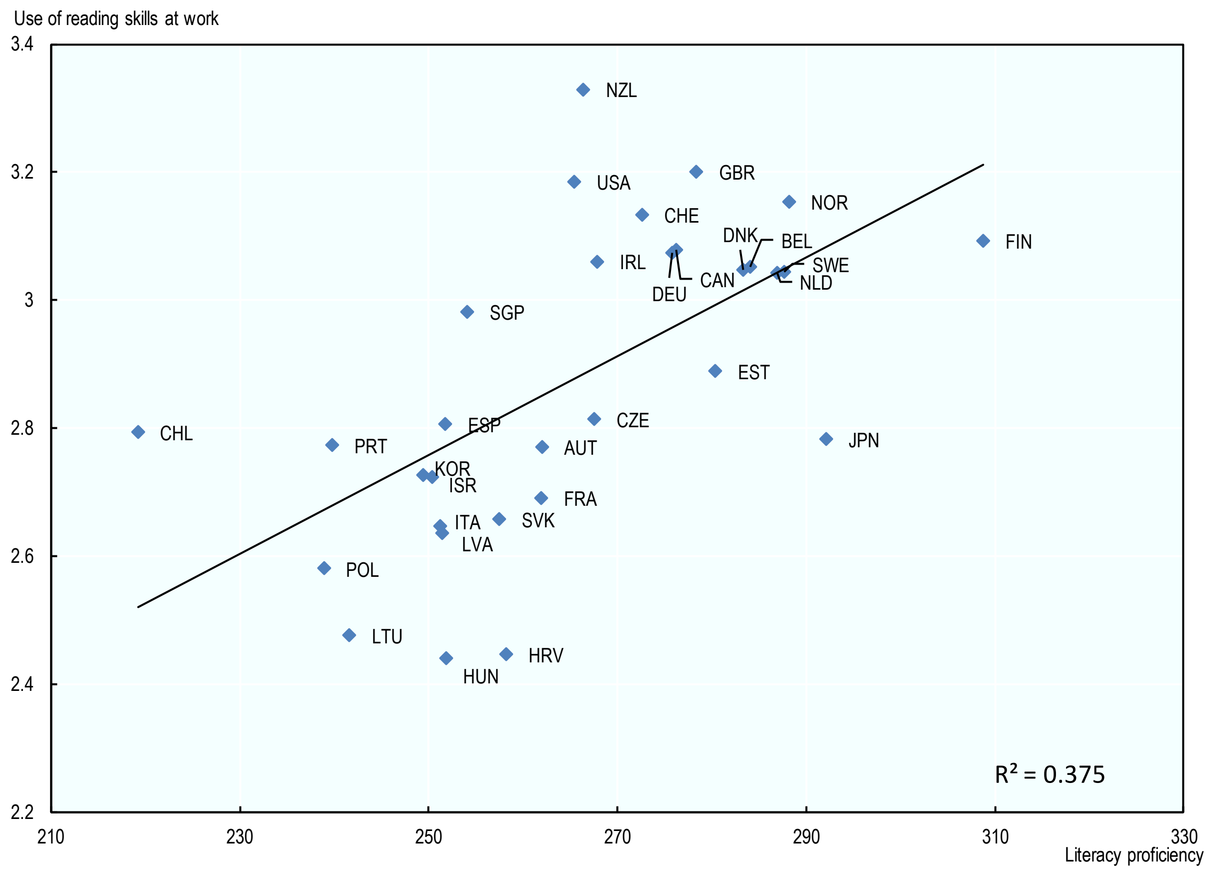
Despite this, policy frameworks have been slow to address the demand side of skills use in a systematic way. Notable exceptions exist; for example, Singapore's SkillsFuture Enterprise Credit encourages employers to support projects aimed at improving skills utilisation (OECD, 2019[7]). Nevertheless, most national strategies still prioritise skills supply. The challenge going forward is to develop policies that do more than simply expand the skill base. Governments, employers, and social partners need to focus on the conditions that enable the productive use of skills. If skills are to function as genuine levers of productivity and inclusion, then greater attention must be paid to how they are deployed and not just acquired.

The broken link between skills proficiency and skills use

A decade after the last major analysis of skills use based on PIAAC data, the most recent results from 2023 in Figure 1.1 continue to show no strong positive correlation between the average proficiency of adults in literacy or numeracy and the frequency with which these skills are used in the workplace (see Box 1.1 for details on how PIAAC measures skills use).[2] In other words, countries with higher average skill levels do not necessarily report more frequent use of those skills at work. This weak association suggests that factors beyond skills proficiency play a critical role in shaping how skills are utilised.[3] The mismatch may reflect structural issues in the labour market, including limited availability of high-skill jobs, underemployment, or inefficient allocation of talent. They can also arise from organisational practices that do not fully leverage employees' capabilities, or from cultural and institutional factors that influence the nature of tasks performed at work. At the same time, the opposite pattern can be found as well. For instance, New Zealand ranks 15th in terms of average literacy proficiency but leads all OECD countries in the frequency of reading skills use at work. This indicates that, despite more moderate skill levels, New Zealand's labour market and workplace environment more effectively exploit literacy skills into daily work tasks.

Figure 1.1. Literacy proficiency and use of reading skills at work

Average proficiency scores and average skills use at work among the working 16- to 65-year-old population



Note: R-squared (R^2) indicates how well the average literacy proficiency explains the variation in the use of reading skills at work across countries. For instance, R^2 =0.37 means that only 37% of the differences in reading use can be attributed to differences in proficiency scores. For consistency, the country name is reported for Belgium and the United Kingdom, even if the Survey of Adult Skills is conducted only at subnational level – namely in the Flemish region and in England, respectively.
Source: 2023 Survey of Adult Skills.

Box 1.1. Measuring skills use in the Survey of Adult Skills

The Survey of Adult Skills is widely recognised for its unique assessment of adult proficiency in literacy, numeracy, and adaptive problem solving. This self-administered assessment (which takes about two hours to complete) is conducted through a series of carefully designed items that directly evaluate individuals' abilities to understand, interpret, and apply information in practical contexts. Less well known, however, is that, in its background questionnaire, PIAAC also gathers standardised, cross-country data on how often these skills are used in both work and everyday settings.

Specifically, PIAAC captures the frequency with which adults carry out tasks involving core information-processing skills – such as reading, writing, numeracy, ICT use, and problem solving – as well as seven additional generic workplace skills – task discretion, learning at work, influencing, co-operation, self-organisation, dexterity, and physical skills.[1] Respondents report how often they perform specific tasks associated with each skill.[2] Task frequency is scored on a five-point scale: 1 (never), 2 (less than once a month), 3 (less than once a week but at least once a month), 4 (at least once a week but not every day) 5 (every day).[3]

Skills use indicators are derived by aggregating multiple task indicators to enhance the robustness of the composite measures (Table 1.1). More specifically, composite indices for each skill type are generated by summing responses to the relevant task items, producing a semi-continuous scale between 1 and 5. A higher score indicates more frequent application of the corresponding skill. Internal consistency of these scales is verified using Cronbach's Alpha to ensure that the selected tasks appropriately reflect the underlying skill construct (see Quintini (2014[3]) and Marcolin, Miroudot and Squicciarini (2019[8]) for a similar approach).[4]

Table 1.1. Indicators of skills use at work in PIAAC Cycle 2

Indicator	PIAAC Cycle 2 variables
	Information-processing skills
Reading	In your current job, how often do you usually: • read directions or instructions? • read letters, memos or e-mails? • read articles in newspapers, magazines or newsletters? • read books, scholarly publications, or articles in professional journals? • read manuals or reference materials? • use maps, plans or GPS for finding directions and locations?
Writing	In your current job, how often do you usually: • write letters, memos or emails? • write reports or articles? • fill in forms?
Numeracy	In your current job, how often do you usually: • undertake calculations, such as calculating prices, costs or quantities? • undertake measurements such as lengths, weights, temperature, dosages, areas or volumes? • read and prepare charts, graphs or tables? • use advanced mathematics or statistics? • read bills, invoices, bank statements or other financial statements?
ICT skills	In your current job, how often do you usually: • communicate with others (e.g. via emails, social networking sites, or internet calls)? • access information (e.g. use a search engine, find information, or read documents)? • create or edit electronic documents, spreadsheets or presentations? • use specialised software (e.g. for computer-aided design, for processing or analysis of data, sound and images, or quality control)? • use a programming language to programme software or websites?
Problem solving	How often are you usually confronted with complex problems that take at least 30 minutes to find a good solution?
	Generic skills
Task discretion	To what extent can you choose or change: • the sequence of your tasks? • how you do your work? • the speed or rate at which you work?
Learning at work	To what extent can you choose or change how often does your current job involve: • learning new things? • learning-by-doing from the tasks you perform? • keeping up to date with new products or services?
Influencing skills	How often does your current job usually involve: • instructing, training or teaching people? • making speeches or giving presentations in front of five or more people? • persuading or influencing people? • negotiating with people either inside or outside your firm or organisation?

Co-operative skills	In your current job what proportion of your time do you usually spend co-operating or collaborating with co-workers?
Self-organising skills	How often does your current job usually involve: • planning your own activities? • organising your own time?
Dexterity	How often does your current job usually involve using hands or fingers for precision work?
Physical skills	How often does your current job usually involve working physically for a long period?

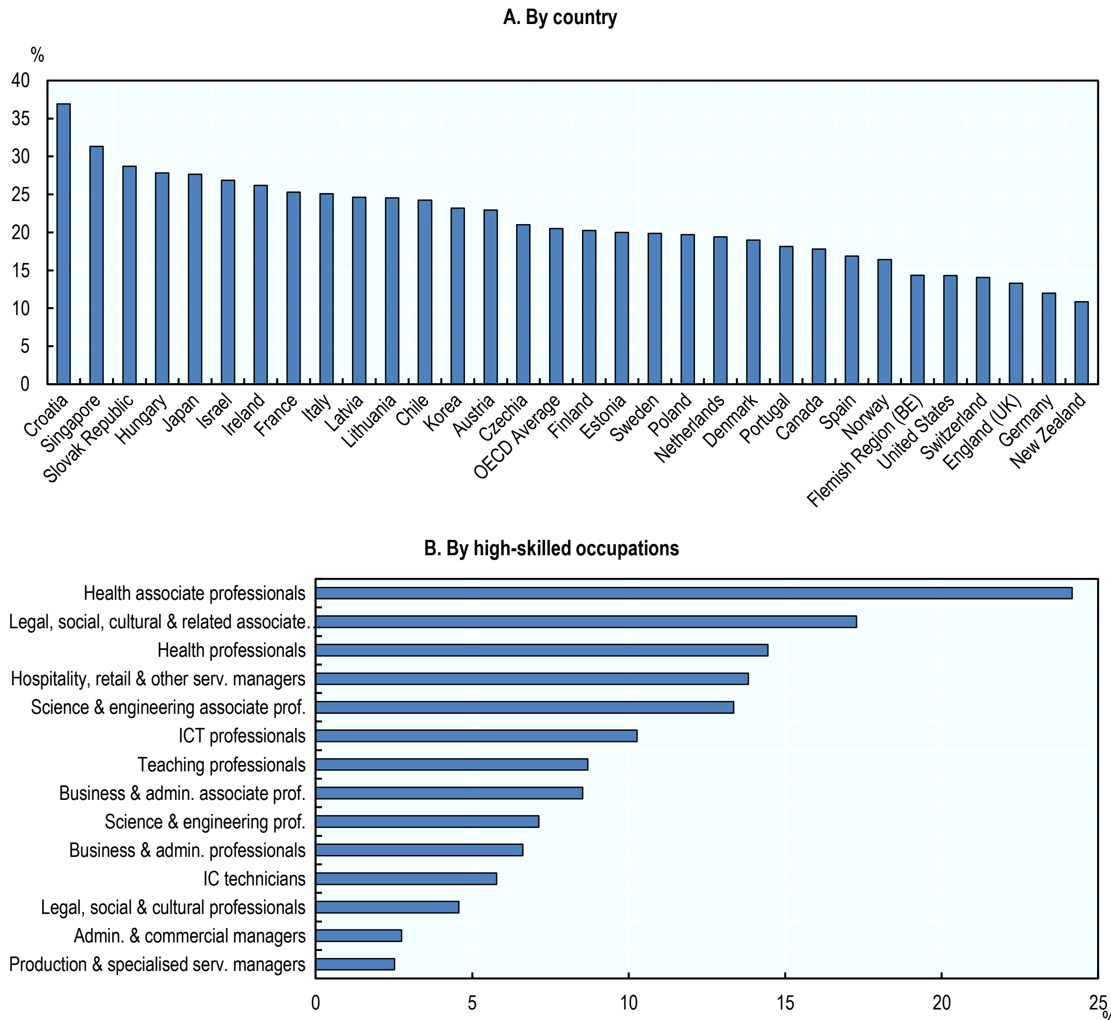
Note: For the actual identifier code of the selected PIAAC variable, refer to the Annex.
1. The report refers to these indicators as "skills", including dimensions such as task discretion and self-organisation. This choice follows established practice in the skills measurement and labour-market literature, where these constructs are commonly conceptualised and labelled as skills rather than solely as job characteristics or working conditions. Major international skills taxonomies, such as O*NET and ESCO, explicitly classify comparable constructs (e.g. autonomy, self-management, planning, influencing others, and co-operation) as skills or skill-related competencies. Using the term "skills" therefore ensures consistency with these widely used frameworks and facilitates comparability with other empirical and policy-oriented analyses, while recognising that some of these skills are expressed and developed through the organisation of work and task allocation.
2. From a conceptual perspective, work tasks can be described in a number of ways (OECD, 2013[9]): by looking at their frequency (the frequency with which a given task is performed), complexity (the level of difficulty required to perform the task successfully) or criticality (the importance of the task to the perform the job). The Survey of Adult Skills adopts frequency as the primary indicator for assessing skill requirements, since it is generally more objective and easier for respondents to recall, which reduces measurement bias. By contrast, the perceived complexity of a task can depend on multiple situational factors and may be influenced by subjective judgement. For example, respondents are usually able to report how often they read work related documents, but the complexity of that reading depends, among the others, on the nature of the documents, their technical content and length. It is, however, important to recognise that, while measures of skills use based on frequency (such as those collected in PIAAC) provide a valid indication of workplace skill demands, for certain occupations the complexity or criticality of specific tasks may depend on contextual conditions that frequency measures alone cannot fully capture.
3. As questions measuring ICT skills use are only posed to respondents who indicate prior computer use, very few respondents report never using ICT skills in the workplace. This leads to a distribution that differs from other skills use scales, and therefore the ICT-at-work scale should be interpreted accordingly.
4. Another strand of the literature computing skills use indices with PIAAC data relies on item response theory (IRT) (see, for instance, OECD (2019[10])). This technique estimates the probability with which the respondent gives a certain answer to the underlying questions ("items"). A set of skills use indices based on IRT is available in the PIAAC Public Use Files (PUFs) for researchers to explore.

Another way to demonstrate the issue of skill underutilisation is to examine the share of workers who demonstrate high levels of literacy proficiency – specifically, those scoring at Level 4 or above – but who make limited use of these skills in their jobs. These individuals fall into the bottom third (tercile) of workplace reading use, despite having the capacity for much more demanding tasks. This mismatch highlights a significant pool of untapped potential: workers who possess strong skills but are not given opportunities to apply them in their day-to-day work.

Panel A of Figure 1.2 illustrates that this is a widespread phenomenon across all countries participating in the second cycle of the Survey of Adult Skills. In every country, at least 10% of highly proficient workers hold jobs that require very little use of their proficiency. In certain countries, such as Croatia and Singapore, this figure rises dramatically – up to one-third of high-skilled workers are not using their literacy skills to their full extent on the job. Panel B examines high-skilled occupations, which may be more likely to entail frequent literacy and reading tasks compared to elementary jobs. The evidence demonstrates that even within these occupations, underutilisation persists. For example, almost one-quarter of health associate professionals with high literacy proficiency scores fall in the lowest tercile for reading use at work. Whatever the cause of such underutilisation of talent, the result is a missed opportunity for both individuals and economies: skills that are developed but not deployed represent lost productivity, lower job satisfaction, and diminished returns on investment in education and training.

Figure 1.2. Share of workers with underutilised skills

Percentage of the working 16- to 65-year-old population who scores at or above Level 4 in literacy but is in the bottom tercile in terms of using reading skills at work



Note: Panel B covers only high-skilled occupations, i.e. those with ISCO 1-digit occupation codes 1 to 3, and presents them at 2-digit level for more granularity.
Source: 2023 Survey of Adult Skills.

Skills use across countries

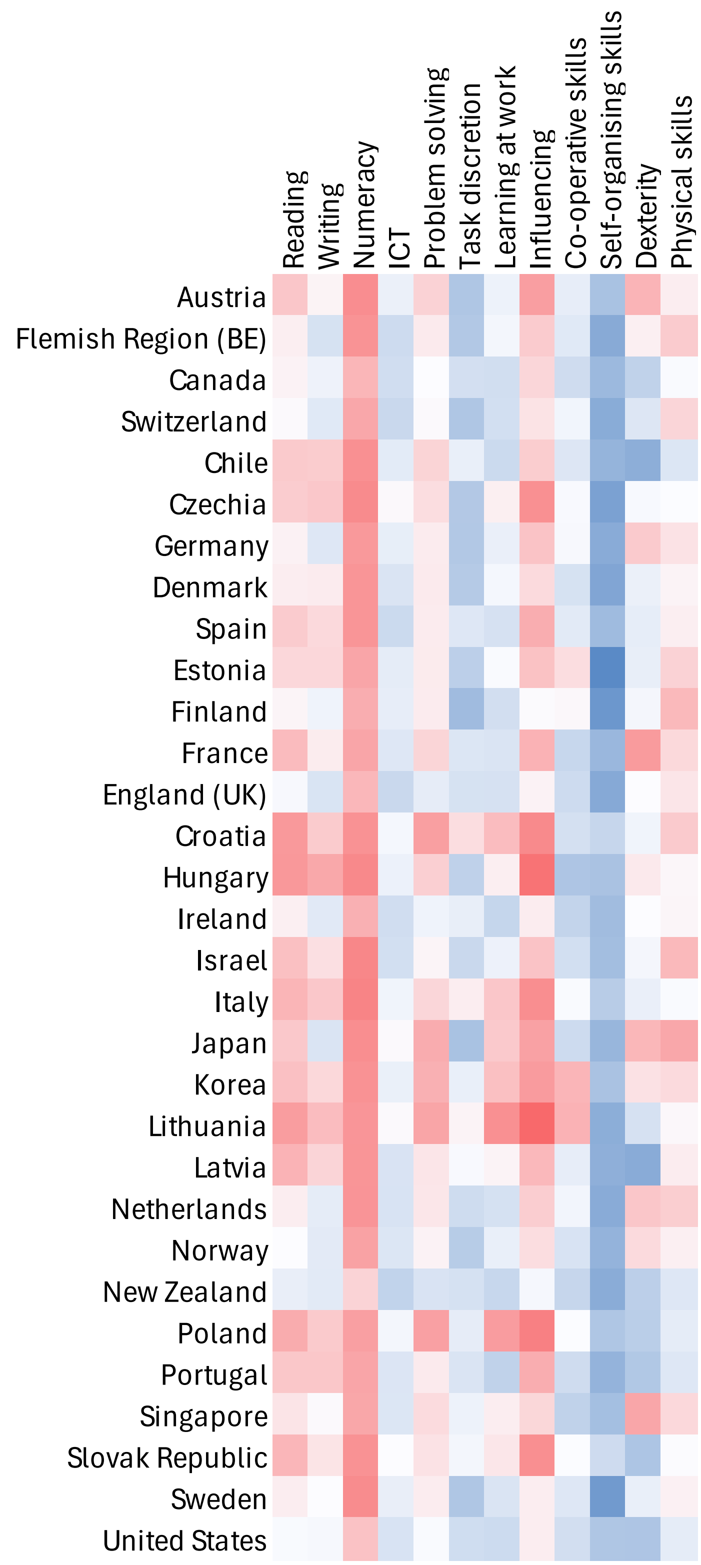
According to the most recent cycle of the Survey of Adult Skills of 2023, self-organising skills are the most commonly used in the workplace in nearly all countries surveyed (Figure 1.3). In most cases, the reported frequency of using self-organising skills exceeds 4 out of 5, indicating they are used at least weekly, though not necessarily every day. Task discretion – i.e. the ability to make independent decisions about the order and speed of one’s tasks – is also reported very frequently in a majority of countries, underscoring the importance of personal initiative and self-management in modern labour markets. Taken together, self-organising skills and task discretion reflect a worker’s capacity to plan tasks and adapt to changing circumstances without constant supervision. As job roles become more autonomous and less routine, employers increasingly value individuals who can take proactive responsibility for their own performance and development (Autor, Levy and Murnane, 2003[11]).

Co-operative skills are also among the most frequently used in workplaces across the countries surveyed by PIAAC. This aligns with recent labour market research (e.g. Deming (2017[12])), which shows that social skills – such as co-operation – are becoming increasingly valuable. By enabling more efficient collaboration, these skills help reduce co-ordination costs and support greater adaptability in response to changing workplace conditions. Contrary to the assumption that modern jobs routinely demand high levels of analytical reasoning, the deployment of problem-solving skills at work remains less frequent than that of other skills. On average, workers across the PIAAC sample report being confronted with complex problems less than once per week, with only 13% of them using problem-solving skills daily.

By contrast, numeracy is the least frequently used skill in the workplace in the majority of countries participating in the second cycle of the Survey of Adult Skills, with 24 out of 31 countries reporting the lowest average frequency of use for this skill. In no country does the average reported use of numeracy at work exceed a score of 3 on the survey scale, which corresponds to less than once per week. This finding suggests that, despite its foundational nature, numeracy plays a relatively limited role in the day-to-day tasks of most workers.

More broadly, the data indicate that information-processing skills – such as reading, writing, and numeracy – are employed less frequently on the job than generic skills.[4] In today's labour market, which is increasingly characterised by collaborative, service-oriented, and dynamic work environments, workers more commonly engage in activities that emphasise teamwork and autonomy. Academic research supports this shift in work practices. Studies such as Autor (2015[13]), who documents the declining relevance of routine cognitive tasks (such as calculation and record-keeping) in favour of non-routine interpersonal and analytical work, highlight a structural transformation in skill utilisation patterns.

Figure 1.3. Skills use by country



Note: The heatmap uses a blue-white-red colour scale to illustrate the relative use of skills in the workplace across countries. Blue indicates above-average use, white represents average use, and red signifies below-average use. The intensity of the colour corresponds to the degree of deviation from the overall average.
Source: 2023 Survey of Adult Skills.

Figure 1.4 and Figure 1.5 present the average use of information-processing skills and generic skills at work, by country (while this analysis focusses on workplace practices, Box 1.2 discusses the relationship between skills use at work and in everyday life). Interesting patterns emerge from the comparison between countries. For example, while reading and writing are both integral components of literacy, the data reveal that countries often exhibit different patterns in the use of these skills. Notably, high use of one skill does not necessarily imply high use of the other. This divergence highlights the complex and context-dependent nature of workplace literacy.

For instance, workers in Belgium report, on average, using writing skills almost every week, ranking first overall in terms of writing use in the workplace. In contrast, they use reading skills at least once a month but less than once a week, placing Belgium 10th out of 31 countries for reading use at work. These disparities can arise from differences in job structures, sectoral compositions, and workplace practices across countries. For example, a workforce heavily concentrated in administrative or managerial roles may require more writing – such as drafting emails, reports, or documentation – than reading, particularly if much of the information is communicated verbally. Conversely, jobs in fields such as education, healthcare, or technical services might require more reading of complex texts, regulations, or technical manuals than original writing. Furthermore, cultural norms around communication can influence how literacy skills are deployed. In some countries, concise oral communication may be preferred over written documentation, or vice versa (Richardson and Smith, 2007[14]; Ortiz, Region-Sebest and MacDermott, 2016[15]).

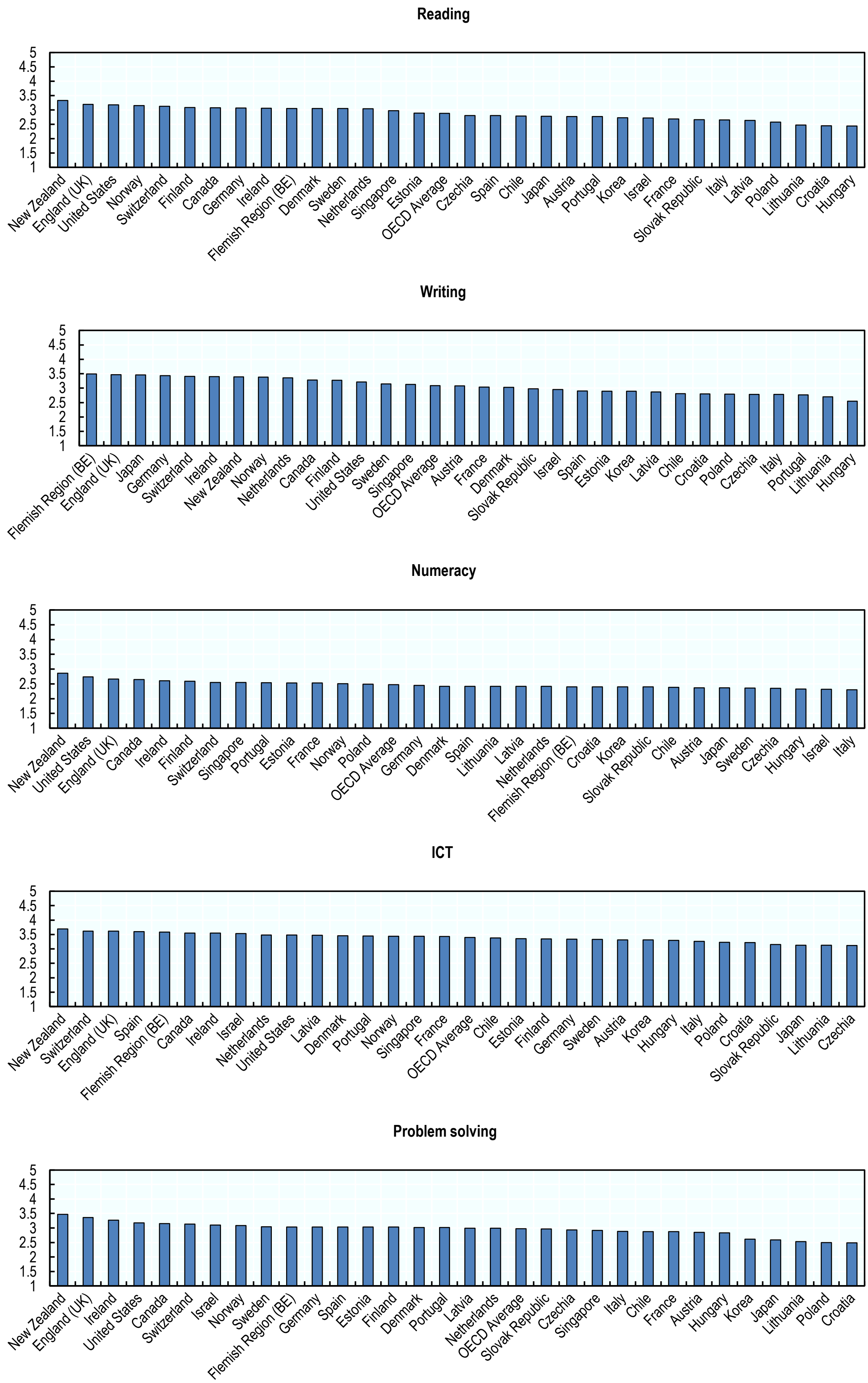
The case of numeracy is particularly noteworthy. Not only, as previously discussed, does numeracy emerge as the least frequently used skill at work, but it also exhibits a remarkable consistency across countries: the average frequency of numeracy use hovers around 2.5 on the 5-point scale, with minimal variation across countries. One explanation for this uniformity may lie in the occupational distribution of numeracy-intensive tasks. Numeracy skills – such as performing arithmetic calculations, interpreting tables and graphs, or estimating quantities – are not universally embedded in the day-to-day activities of most workers. Rather, these skills are concentrated in specific technical roles in sectors like engineering, finance, accounting. In contrast, large portions of the workforce in industries such as retail, hospitality, healthcare, personal services, and administrative support may rarely need to engage in explicit numerical tasks on a regular basis.[5]

Dexterity use exhibits the highest standard deviation of the 12 skills assessed in the Survey of Adult Skills. This indicates that the frequency with which dexterity is used in the workplace varies more widely across countries than any other skill. For instance, in countries like Chile and Latvia tasks requiring manual precision are performed at least weekly, if not daily, with average use ratings close to 4 on a 5-point scale. Conversely, in countries such as France and Singapore, dexterity ranks as the least used skill, with an average score of approximately 2.5. This level of use implies that tasks involving dexterity occur infrequently – perhaps only once a month or less in many occupations.

This stark contrast highlights the diverse economic structures among OECD Member states. Countries with a significant share of employment in manufacturing tend to emphasise dexterity more heavily, whereas those with economies oriented around information technology and professional sectors – commonly referred to as knowledge economies – place less emphasis on manual skills (Kunst, 2020[16]). These patterns are consistent with findings from the economic literature, which underscore how occupational structures and technological advancement shape skill demand across national labour markets (Sasso and Ritzen, 2019[17]).

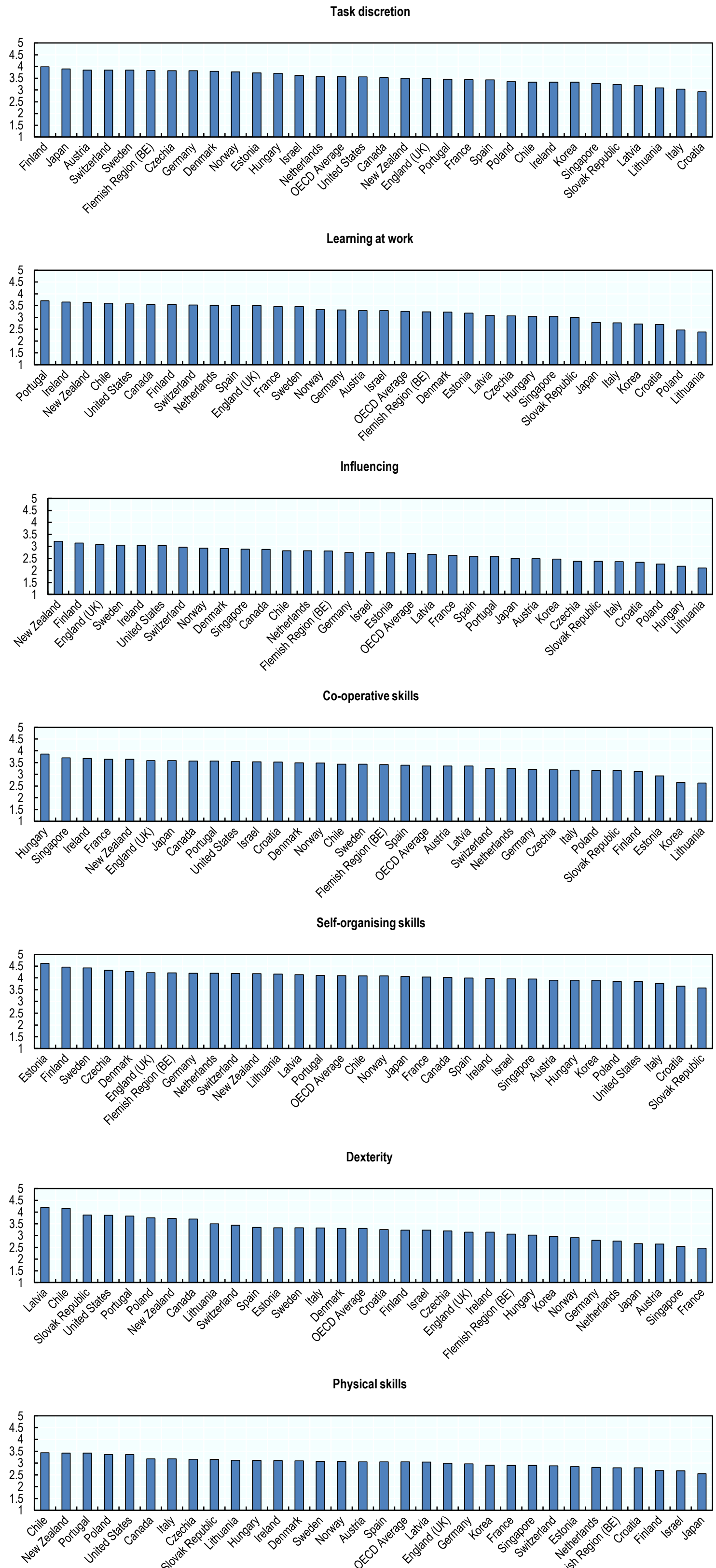
More broadly, examining how countries rank in the use of various skills in the workplace reveals several interesting patterns. New Zealand stands out as the country with the most frequent use of a wide range of skills. Among the 31 participating countries, it ranks first in the use of reading, numeracy, ICT, problem solving, and influencing skills, and it is among the top five for use of learning at work, co-operative skills, and physical skills. The United Kingdom, instead, performs strongly in the use of information-processing skills (consistently ranking among the top three), but it displays significantly lower use of generic skills, such as task discretion, learning at work, and manual dexterity. Some countries demonstrate a more mixed profile. For instance, Finland ranks at the top in the use of task discretion, self-organisation, and influencing skills, yet falls below the average for ICT and co-operative skills use. Similarly, in the United States, workers report high use of reading, numeracy, problem solving, and dexterity, but rank among the lowest for self-organising skills.

Figure 1.4. Average use of information-processing skills at work



Source: 2023 Survey of Adult Skills.

Figure 1.5. Average use of generic skills at work



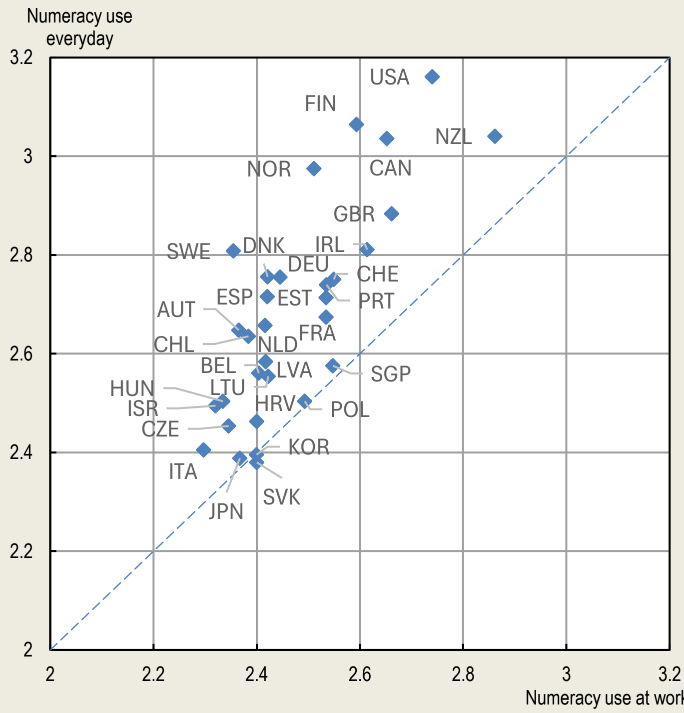
Source: Survey of Adult Skills (Cycle 2).

Box 1.2. The relationship between skills use at work and in everyday life

While this report primarily examines the use of skills in the workplace, the Survey of Adult Skills also gathers information on how adults apply reading, writing, numeracy, and ICT skills in their everyday lives. To explore how skills are used across different contexts, Figure 1.6 shows the representative case of the relationship between the use of numeracy skills at work and in everyday life. The data reveal a positive correlation between these two domains at the country level (R-squared = 0.62). In general, countries where adults frequently use numeracy in their jobs also report higher levels of numeracy use at home.

However, the two are not perfectly aligned. Across the PIAAC sample, adults often report greater use of numeracy in everyday life than in the workplace. This gap is particularly pronounced in the Nordic countries – such as Finland, Norway, and Sweden – where the average adult reports using numeracy skills at home approximately 0.50 points more (on a 1-to-5 scale) than at work. Several factors may help explain this pattern. First, in many advanced economies, individuals are increasingly responsible for managing complex aspects of their personal and household affairs – including budgeting, financial planning, and interpreting utility bills. These activities routinely require the application of numeracy skills such as estimation, calculation, and data interpretation. Second, the digitalisation of public services and commerce has shifted more numeracy-intensive tasks to individuals. Online banking, e-government portals, and e-commerce platforms often demand a basic proficiency in numeracy for tasks like verifying transactions, comparing prices, and assessing service terms. Third, in many work environments, especially in sectors characterised by high levels of automation, opportunities for employees to regularly use numeracy skills may be limited (Hodgen and Marks, 2013[18]). Lower-skilled jobs, in particular, may involve tasks that are either repetitive or supported by technology, reducing the need for active numerical reasoning. While these interpretations help to frame the observed differences, the magnitude of the gap in some countries suggests that further analysis would be needed to fully understand the underlying drivers.

Figure 1.6. Correlation between use of numeracy at work and in everyday life, by country



Note: The dashed line represents the 45-degrees line (and not the trend line). R-squared (R^2) indicates how well the average numeracy use at work explains the variation in the use of numeracy skills in everyday life across countries. For instance, $R^2 = 0.62$ means that 62% of the differences in numeracy use everyday can be attributed to differences in numeracy use at work.
Source: 2023 Survey of Adult Skills.

How workers' and jobs' characteristics relate to skills use

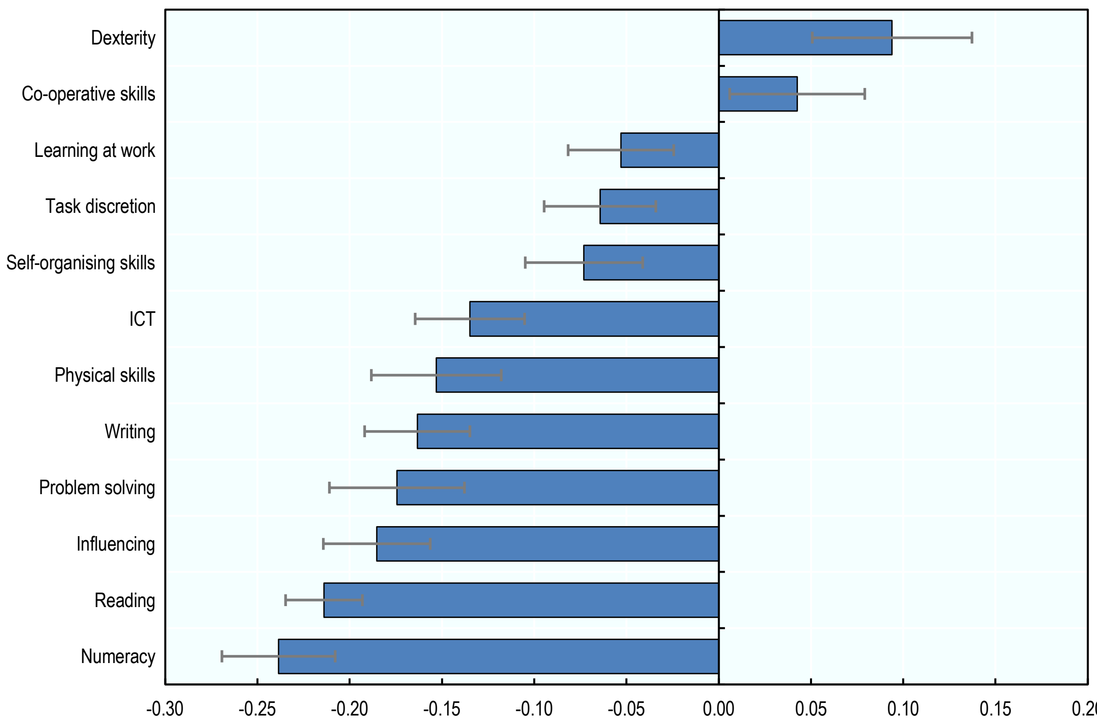
To better understand the factors influencing skills use in the workplace, it is essential to examine how individual and job characteristics shape the way workers translate their proficiency into on-the-job skill deployment.

Figure 1.7 presents the estimated average difference in skills use between women and men, controlling for age, education, literacy proficiency, occupation, industry, firm size, full-time status, contract type, and public versus private sector employment. On average, women use their skills less frequently than men in the workplace, even when they possess similar levels of proficiency and hold similar occupations. For instance, women score 0.24 points lower than men in the use of numeracy skills, a difference that remains significant after accounting for all covariates. This could reflect persistent gender segregation within occupations – e.g. within the same occupational titles, men may disproportionately occupy roles requiring quantitative tasks (such as budgeting or data analysis). Dexterity is the only skill that women report using slightly more frequently than men, though the difference is modest. Indeed, women may be more represented in roles requiring fine motor skills (e.g. precision work, manual tasks in healthcare or services), even within similar occupational categories.

Overall, these results point at the fact that task assignments in the workplace may be gender-biased, even after controlling for observable characteristics (Pető and Reizer, 2021[19]; Hauret et al., 2023[20]). This task-level segregation can reinforce gender disparities in skill development, productivity, and pay. The fact that men and women in the same occupation are routinely assigned different types of work limits opportunities for women to accumulate experience in high-value or high-visibility tasks (such as data analysis, decision making, or problem-solving) that are more likely to lead to promotion and wage increases (De Pater, Van Vianen and Bechtoldt, 2010[21]; Babcock et al., 2017[22]; Bizopoulou, 2019[23]).

Figure 1.7. Women's use of skills at work

OLS coefficients



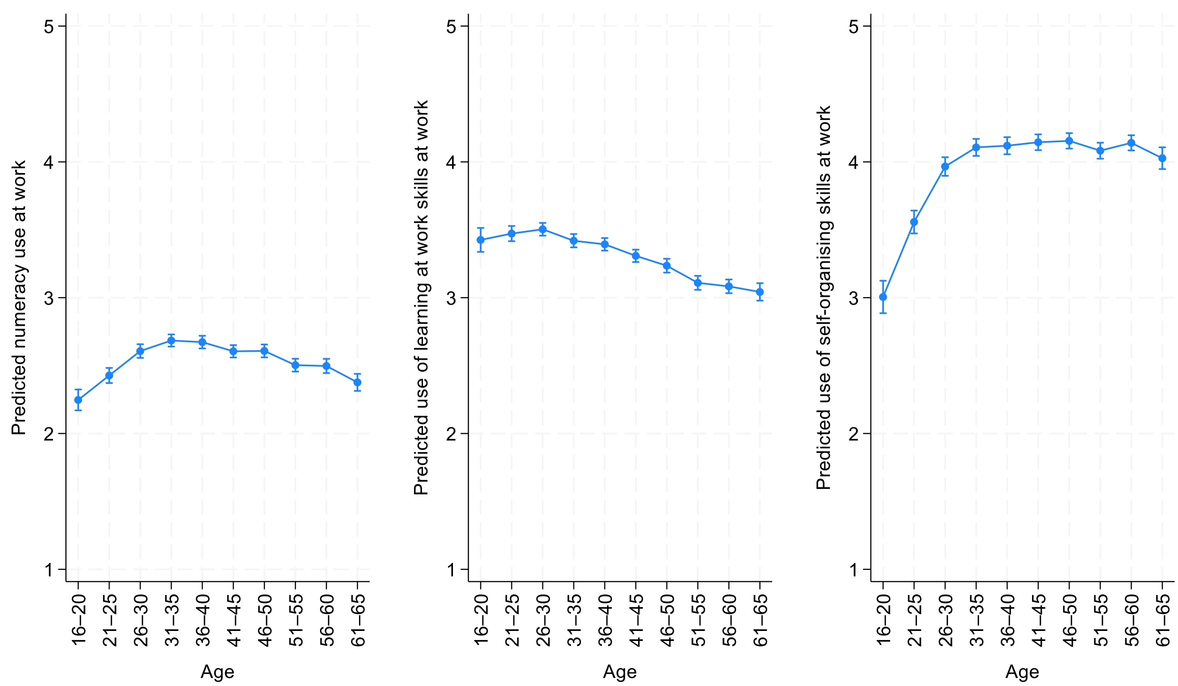
Note: The Figure represents the coefficient of OLS regressions of skills use on gender. Coefficients are adjusted for age, age squared, educational attainment, literacy proficiency, occupation, industry, firm size, full-time work, permanent contract, public employment, and country fixed effects. The Figures also includes standard error bars.
Source: 2023 Survey of Adult Skills.

Studies on adult skills consistently finds that older adults (often defined as individuals aged 55 to 65) tend to exhibit weaker proficiency in information-processing skills such as literacy, numeracy, and adaptive problem-solving, relative to younger age groups (Picchio, 2015[24]; Paccagnella, 2016[25]; OECD, 2025[26]). These age-related differences persist even after accounting for observed differences in education level and field of study. However, while the decline in cognitive performance with age is well documented, the relationship between age and the use of skills in the workplace is less straightforward. One might expect an ageing effect – that is, the natural decline in certain cognitive functions, including memory and information-processing speed – to result in lower skills use at older ages. Yet, empirical evidence does not suggest a uniform pattern of decline. Instead, skills use across age groups appears to be heterogeneous and task dependent.

Figure 1.8 illustrates this complexity by showing varied trajectories of skills use with age. For some skills, such as numeracy, use follows an inverted U-shaped pattern: it tends to increase during mid-career as individuals accumulate experience and confidence, before declining in later years, potentially due to cognitive ageing or changes in job roles.[6] For other skills, such as learning at work – i.e. the extent to which workers acquire new knowledge or update their skills – use tends to decline steadily with age. This may reflect reduced training opportunities, including informal learning from peers (as found by OECD (2025[26])), or lower motivation to engage in upskilling. Conversely, the use of self-organisation skills tends to increase with age and then stabilise. This pattern likely reflects the accumulation of job experience, seniority, and autonomy over time, which can compensate for declining cognitive skills by enabling older workers to draw on their expertise.

These heterogeneous patterns highlight that age-related differences in skills use cannot be solely attributed to ageing. Workplace dynamics, job design, and institutional factors – such as access to training and career progression pathways – also play critical roles in shaping how skills are used throughout the life course (Hanushek et al., 2025[27]).

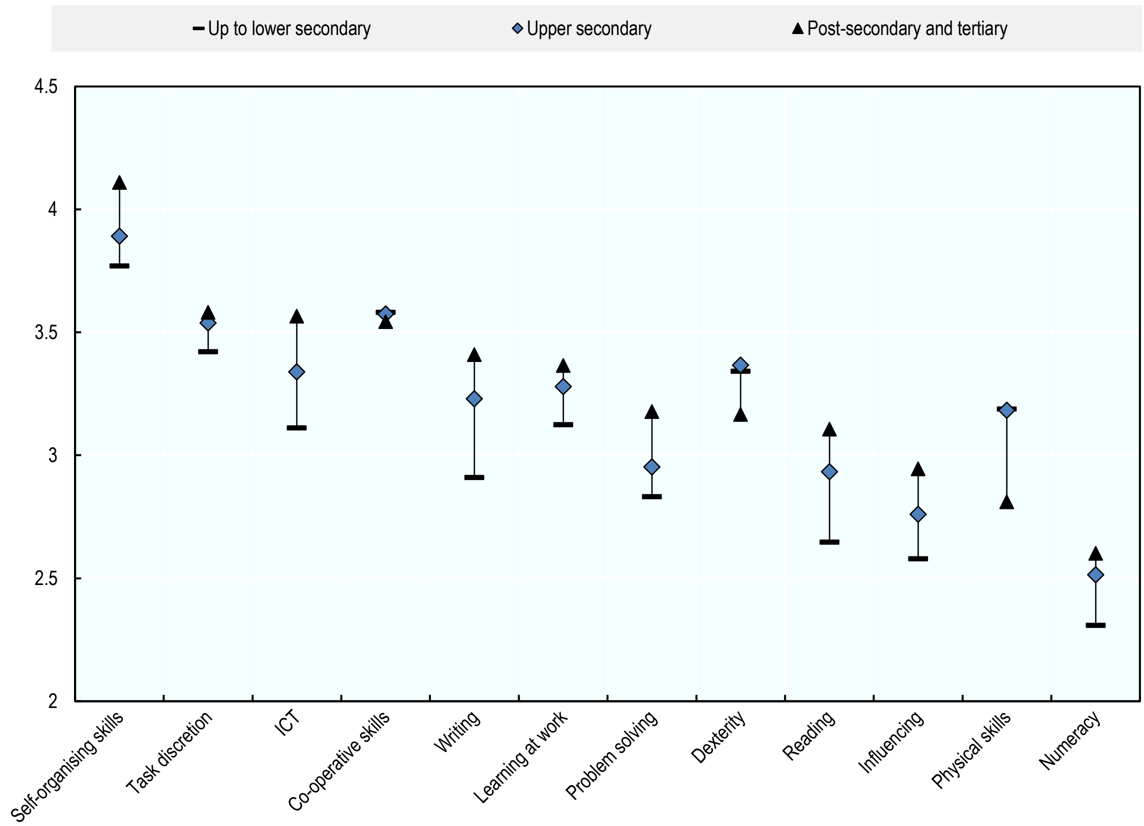
Figure 1.8. Predicted use of selected skills at work by age



Note: The Figure displays the predicted skills use by age, based on a weighted regression model. Confidence intervals indicate the precision of each estimate.
Source: 2023 Survey of Adult Skills.

Figure 1.9 presents the relationship between educational attainment and the predicted use of various workplace skills, controlling for a set of individual and job-level characteristics.[7] The data reveal that skills use does not increase systematically with higher levels of educational attainment. Instead, the pattern varies markedly across domains. For several skills, such as task discretion, learning at work and numeracy, individuals with post-secondary or tertiary education report frequency of use comparable to those with upper secondary qualifications once occupation, proficiency and other characteristics are taken into account. In contrast, substantial differences by educational attainment emerge for skills such as self-organising, problem solving and influencing skills, where tertiary-educated workers demonstrate notably higher levels of use. While this finding suggests that tertiary education does not always translate into higher on-the-job skills use, it still underscores the critical importance of achieving at least upper secondary education as a minimum threshold for participation in more skill-intensive work. It also highlights the challenge of addressing low skills use among workers with lower levels of formal education – an issue with direct implications for productivity, social mobility, and lifelong learning policy.

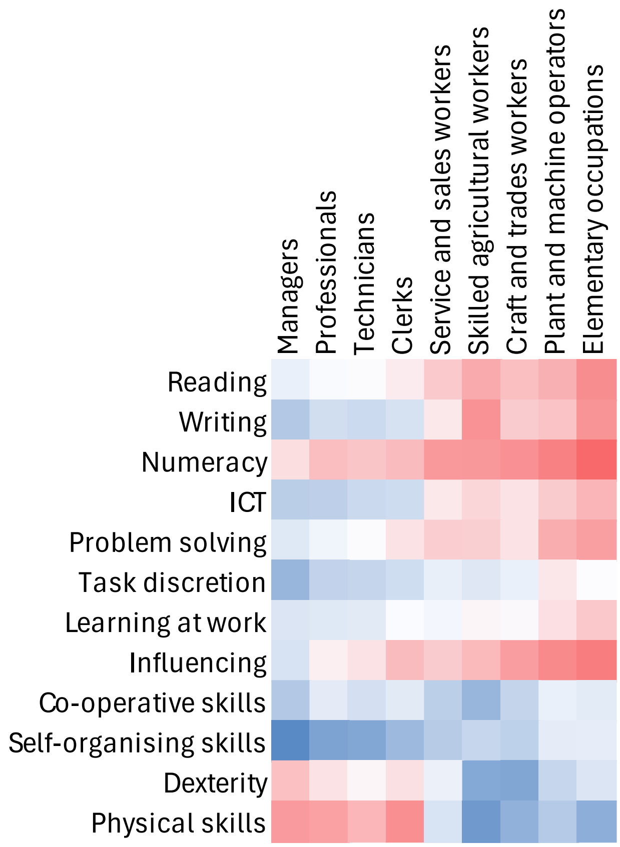
Figure 1.9. Predicted skills use at work by educational attainment



Note: The Figure displays the predicted skills use by educational attainment, based on a weighted regression model. Coefficients are adjusted for gender, age, age squared, literacy proficiency, occupation, industry, firm size, full-time work, permanent contract, public employment, and country fixed effects.
Source: 2023 Survey of Adult Skills.

The average use of skills across occupations generally aligns with expectations (Figure 1.10). Workers in high-skilled occupations – such as managers, professionals, and technicians – tend to make more frequent use of a broad range of skills. These include cognitive (e.g. writing) and social (e.g. influencing) skills, which are integral to complex decision-making tasks. In contrast, lower-skilled occupations, including plant and machine operators and workers in elementary occupations, rely more heavily on physical and manual dexterity skills. Interestingly, co-operation skills are frequently used across all occupational groups. This underscores the pervasive importance of teamwork and interpersonal collaboration in today's labour market, regardless of skill level or occupation.

Figure 1.10. Predicted skills use at work by occupation



Note: The Figure displays the predicted skills use by occupation, based on a weighted regression model. Coefficients are adjusted for gender, age, age squared, literacy proficiency, educational attainment, industry, firm size, full-time work, permanent contract, public employment, and country fixed effects. The heatmap uses a blue-white-red colour scale to illustrate the relative use of skills in the workplace across occupations. Blue indicates above-average use, white represents average use, and red signifies below-average use. The intensity of the colour corresponds to the degree of deviation from the overall average (i.e. the average of all skills and occupations together).
Source: 2023 Survey of Adult Skills.

An analysis of skills use across industries reveals significant variation in the demand for different skills depending on the nature of work. Table 1.2 presents the relative ranking of skill intensity in 20 sectors (with a rank of 1 referring to the most used skill and a rank of 12 pointing to the least used one). In nearly all sectors, self-organising, task discretion, and co-operative skills rank among the most used (commonly ranked in the top 3). In line with previous findings from this Chapter, reading, writing, and particularly numeracy are infrequently used at work across most sectors. For example, numeracy is the least used skill (rank 12) in 13 of the 20 sectors, including manufacturing, retail, and education. Reading and writing also see low usage outside of a few high-skill services like real estate and public administration. ICT skills are highly ranked (1-3) in financial services, information and communication, and administration and support services, reflecting digitisation in these areas. Conversely, ICT is less used (ranks 7-8) in accommodation and food services and in health. These two sectors use more frequently dexterity and physical skills (ranks 2-4).

Table 1.2. Predicted skills use at work by industry

Ranking of the frequency of use of skills at work in each industry

	Reading	Writing	Numeracy	ICT	Problem solving	Task discretion	Learning at work	Influencing	Co-operative skills	Self-organising skills	Dexterity	Physical skills
Agriculture, forestry & fishery	10	7	12	4	9	2	8	11	3	1	5	6
Mining & quarrying	10	5	11	3	8	4	6	12	2	1	7	9
Manufacturing	10	6	12	4	8	3	7	11	2	1	5	9
Electricity and gas	7	4	10	2	9	3	6	12	5	1	8	11
Water supply & waste management	10	5	12	4	7	2	8	11	3	1	6	9
Construction	10	8	12	4	7	3	5	11	2	1	6	9
Wholesale & retail	10	7	12	5	8	2	4	11	3	1	6	9
Transportation	7	4	12	3	9	2	6	11	5	1	10	8
Accommodation & food services	12	10	11	7	9	5	6	8	1	2	3	4
Info & communication	8	7	11	2	6	3	4	10	5	1	9	12
Financial	8	4	11	2	7	3	5	9	6	1	10	12
Real estate	6	4	10	3	5	2	7	9	8	1	11	12
Professional & scientific	8	5	10	2	7	3	6	11	4	1	9	12
Admin & support services	8	5	12	2	6	3	7	10	4	1	9	11
Public administration & defence	7	3	12	4	8	5	6	10	2	1	9	11
Education	10	7	12	3	11	2	5	9	4	1	6	8
Health & social work	10	5	12	8	9	6	7	11	3	1	2	4
Arts	9	8	12	5	11	3	6	10	2	1	7	4

Note: The Figure displays the ranking of use of skills at work. To construct this ranking, the predicted skills use by industry, based on a weighted regression model, is exploited. Underlying coefficients are adjusted for gender, age, age squared, literacy proficiency, educational attainment, occupation, firm size, full-time work, permanent contract, public employment, and country fixed effects.
Source: 2023 Survey of Adult Skills.

To conclude, the chapter assesses the relationship between a range of job characteristics and the frequency of skills use at work (Table 1.3). Job stability, proxied by the presence of an open-ended (indefinite) contract compared to a temporary or fixed-term arrangement, is positively associated with the use of information-processing skills – particularly writing and problem-solving. This aligns with evidence from OECD (2016[5]), which suggests that stable employment relationships provide more opportunities for skill development and utilisation, likely due to greater investments in training and in tailoring job content by employers. However, no statistically significant differences are observed between permanent and temporary contracts regarding the use of dexterity or physical skills. This may reflect the more routinised nature of these tasks, which are less sensitive to employment duration.

Work schedule arrangements have a substantial effect on skills use. In particular, part-time workers report markedly lower use of virtually all skill categories at work.[8] While employment in the public sector is associated with increased use of reading, dexterity, learning at work, and influencing skills, these differences are relatively modest when compared to the stark contrast between part-time and full-time workers. This suggests that job structure and time commitment may play a more critical role than sectoral affiliation in determining skill utilisation.

The size of the company also plays a significant role. Larger firms tend to promote greater use of information-processing skills such as reading, writing, and problem solving. This may be due to the more complex, hierarchical, and bureaucratic structures of large firms, which often require higher levels of documentation, co-ordination, and analytical capacity. In contrast, smaller firms tend to rely more heavily on dexterity and physical skills, as well as on task discretion and self-organising competencies. The flatter organisational structures and broader role expectations typical of smaller enterprises often necessitate greater autonomy and physical versatility from employees (OECD, 2019[28]).

Table 1.3. Use of skills and job characteristics

OLS coefficients

	Reading	Writing	Numeracy	ICT	Problem solving	Task discretion	Learning at work	Influencing	Co-operative skills	Self-organising skills	Dexterity	Physical skills
Indefinite contract	0.113***	0.195***	0.087*	0.075*	0.152***	0.141***	0.005	0.098**	0.020	0.211***	-0.070	-0.009
Part-time	-0.297***	-0.438***	-0.278***	-0.300***	-0.413***	-0.083*	-0.220***	-0.329***	-0.324***	-0.401***	-0.251***	-0.250***
Public sector employment	0.160***	0.034	-0.026	-0.009	0.083	-0.037	0.090*	0.072*	0.059	0.011	0.146**	0.067
11-49 workers	0.085***	0.088*	-0.001	0.006	0.079*	-0.115***	0.048	0.130***	0.151**	-0.094	-0.050	0.040
50-249 workers	0.122***	0.110**	-0.016	0.073*	0.154***	-0.097**	0.090*	0.201***	0.187***	-0.091	-0.126*	-0.030
250-999 workers	0.138***	0.135**	0.006	0.082	0.183***	-0.124**	0.096*	0.177***	0.231***	-0.137*	-0.131	-0.128*
More than 1 000 workers	0.150***	0.144**	-0.014	0.192***	0.265***	-0.076	0.144**	0.213***	0.273***	-0.087	-0.214*	-0.240***

Note: Coefficients are adjusted for gender, age, age squared, educational attainment, literacy proficiency, occupation, industry, and country fixed effects.
Source: 2023 Survey of Adult Skills.

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Notes

[1] While these effects are not merely anecdotal, economic evidence is limited and dated. Research has linked better use of skills in the workplace to higher job satisfaction and improved well-being, which has

led some analysts to associate skills use with the concept of job quality (Green et al., 2013[29]). There is also evidence that more effective skill deployment contributes to increased productivity in firms (UKCES, 2014[31]), as well as greater innovation, engagement, and investment (Wright and Sissons, 2012[30]). However, more recent evidence is needed on the impact of skills use at work on economic and social outcomes, and this report aims at filling part of this gap.

[2] Throughout this report, caution is required in interpreting results for Poland due to the high share of respondents with unusual response patterns in the second cycle of the Survey of Adult Skills – see note for Poland in the Reader's Companion (OECD, 2024[32]).

[3] In addition, the mismatch may partially reflect the fact that skill proficiency as measured by the Survey of Adult Skills covers a broader range of literacy domains compared to the use of reading skills at work.

[4] It is important to note that not every skill needs to be used intensively in every job. Certain highly skilled workers may be satisfied and highly productive without regularly using certain skills that they possess. This is why this report does not interpret low use of a specific skill in isolation as a problem per se, nor it suggests that individuals should change jobs simply to increase the frequency with which they use a particular skill. The skills-use measures derived from PIAAC are descriptive: they document how skills are used across jobs and workers, not how they should be used. As such, the analysis is intended to inform policy discussions at the aggregate level – for example, about how education systems, training policies, or workplace practices shape opportunities to use skills.

[5] Measuring skills use through self-reporting (like in the Survey of Adult Skills) might also underestimate numeracy if some workers cannot recognise their tasks as requiring numerical skills (e.g. interpreting inventory trends or estimating time and cost). This phenomenon of "invisible numeracy" has been well documented in the literature (Goos et al., 2023[33]). Numeracy is also often embedded in other tasks, such as using software (Jonas, 2018[6]). As a result, respondents may be less likely to report these tasks as involving numeracy, compared to more conscious skills like reading and writing.

[6] Differences in skills use and proficiency among age groups may be also partially driven by cohort effects (OECD, 2025[26]). Cohort (generational) effects stem from the unique conditions each age group experienced growing up – such as the level of access to technology, education systems, labour market dynamics, and public policies. For instance, younger individuals often demonstrate stronger information-processing skills, also because they may have had greater exposure to modern digital technologies during their schooling years.

[7] The baseline specification controls for a detailed set of individual characteristics as well as job attributes, including 1-digit ISCO occupation dummies (10 groups) and 1-digit ISIC industry dummies (21 sections). Given that educational attainment influences occupational sorting, alternative specifications excluding occupation and industry controls were also estimated. The relationship between educational attainment and the predicted use of workplace skills remains qualitatively comparable.

[8] The PIAAC skill-use variables were designed to be applicable to both full-time and part-time workers, as they measure the frequency of engaging in specific tasks rather than total time spent on them. However, it is possible that part-time workers may under-report their use of skills because they have fewer working hours within a typical week or month, which can reduce the perceived frequency of task engagement even when the nature of their work is similar to that of full-time employees.

2 Why skills use matters

This chapter examines whether individuals who make greater use of their skills at work are rewarded differently in the labour market. The analysis focusses on two dimensions. First, the relationship between skills use and wages is assessed in order to identify whether more intensive deployment of skills is associated with higher wages. Second, the potential spillovers onto job satisfaction and the risk of burnout are investigated, recognising that the frequency of skills use may shape not only monetary returns but also wider dimensions of worker well-being.

In Brief

More frequent skills use at work is associated with better economic and non-economic outcomes

- Higher frequency of skills use is associated with higher wages and the relationship is statistically significant even after accounting for individual and job characteristics. Greater use of influencing skills and information-processing skills such as ICT and numeracy is linked to the highest wages, while physical skills are negatively linked to wages.
- The magnitude of the association between wages and skills use differs substantially across countries, suggesting that it might be influenced by institutional arrangements, occupational patterns and the structure of the demand for skills.
- Although women earn lower wages than men with comparable characteristics, for most skills, the returns to use do not differ significantly by gender. This suggests that, once men and women are sorted in jobs that make frequent use of one's skills, they typically receive comparable rewards.
- The association between wages and skills use varies significantly by age, suggesting a relationship between skills use, career progression and seniority wages. This highlights the importance of a life-cycle perspective when assessing the value of skills in the labour market.
- Countries with more unequal distribution of skills use tend to exhibit higher wage inequality. By contrast, greater use of skills is positively correlated with labour productivity, although other unobserved drivers – such as industry structure and institutional quality – may play a larger role.
- Deployment of workers' skills generates intrinsic motivation, with greater skills use linked to higher levels of job and life satisfaction. Use of skills also mitigates job burnout, except in the case of physical skills, whose intensive use is associated with increased risk.

Introduction

The analysis of the returns to skills use at work provides a valuable perspective on the functioning of labour markets and the allocation of human capital. While much research has focussed on the returns to education and formal qualifications (see Psacharopoulos and Patrinos (2018[1]) and Gunderson and Oreopolous (2020[2]) for recent reviews of the literature), the actual utilisation of skills in the workplace may yield more direct insights into the link between skills, wages and productivity. The mere accumulation of skills does not guarantee economic returns if these are underutilised or misallocated relative to job tasks. An analysis of the relationship between skills use and wages, hence, provides a more precise measure of the channels through which individual skills translate into wages, productivity, and subjective well-being.

The expected relationship between skills use and wages rests on the notion that workers who deploy their skills more frequently at work contribute more significantly to outputs and are therefore compensated accordingly. The productivity channel is central, since firms that enable employees to apply their skills would achieve a better match between skills and job tasks and more experimentation. At the same time, skills use is likely to influence job satisfaction and lower turnover, as workers tend to derive greater intrinsic motivation and engagement when their skills are effectively deployed. This may further reinforce productivity outcomes through reduced turnover and stronger commitment to organisational objectives.

Examining these outcomes is relevant for policy and practice. From a policy perspective, understanding the returns to skills use can inform education and training strategies, particularly in relation to skill mismatch and underutilisation of human capital. From a firm-level perspective, it highlights the importance of work organisation and management practices in fostering both performance and employee well-being.

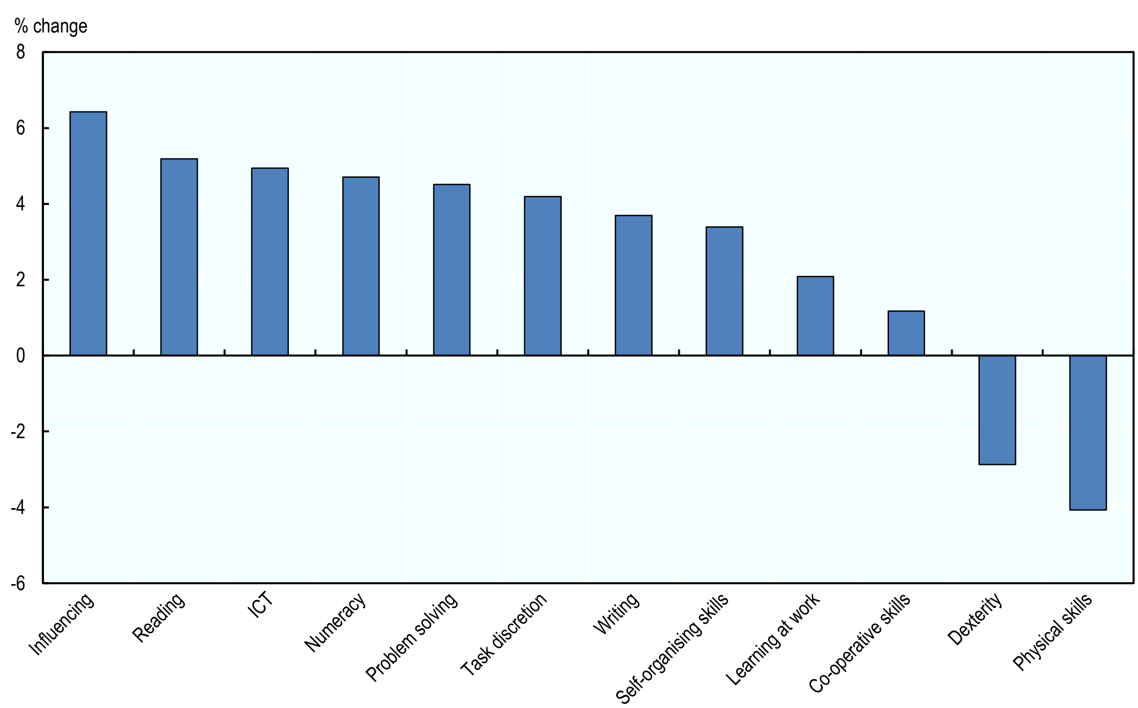
Skills use and wages

More intensive use of skills in the workplace is associated with higher wages and the association is statistically significant (Figure 2.1). Even after controlling for individual and job characteristics, workers who deploy skills more frequently in their daily tasks at work receive higher wages (see Box 2.1 to examine how skills use and skills proficiency are associated differently to wages).[1] This association holds for all skill categories except dexterity and physical skills – which is in line with the findings of previous studies, such as De La Rica, Gortazar and Lewandowski (2020[3]) and Agasisti, Johnes and Paccagnella (2021[4]). This could be partially due to the fact that jobs that rely heavily on physical or manual skills tend to be concentrated in specific sectors with relatively low productivity growth and limited opportunities for wage progression, in contrast to knowledge-intensive sectors (Acemoglu and Autor, 2011[5]).

The largest association between skills use and wages is observed for influencing skills and information-processing skills such as reading, ICT and numeracy.[2] For instance, across countries in the PIAAC sample, a one-standard-deviation increase in the use of influencing skills at work is linked to a 6% increase in hourly wages (everything else, including occupation, being equal). In contrast, the frequency of learning at work or collaborating with colleagues is associated with only a 2% and 1% increase, respectively.

Figure 2.1. Wage returns to skills use

Association of a one-standard-deviation increase in the use of each skill and hourly wages, OLS coefficients



Note: The Figure represents the coefficients of OLS regressions of skills use on wages, weighted by sampling weights. Each bar represents a separate regression. Wages are gross hourly earnings for employed and self-employed individuals, including bonuses, in PPP-adjusted 2022 USD. The wage distribution was trimmed to eliminate the 1st and 99th percentiles. The sample includes only full-time workers aged 25-65. Coefficients are adjusted for gender, immigration background, age, age squared, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment, and country fixed effects. All coefficients are statistically significant (at least at the 5% significance level). Korea is not included in the analysis due to unusual response patterns on wages.
Source: 2023 Survey of Adult Skills.

Box 2.1. Is proficiency more closely associated with wages than the use of skills at work?

To examine whether proficiency in literacy and numeracy affects wages more than the actual use of these skills in the workplace, a Mincer-style wage regression can be estimated (similar to that of Kawaguchi and Toriyabe (2022[6])):

$$\log(wage_i) = \alpha + \beta \cdot proficiency_i + \gamma \cdot use_i + X_i'\delta + \varepsilon_i$$

Equation 2.1.

where $\log(wage_i)$ is the natural logarithm of gross hourly earnings for individual *i* (including bonuses, in PPP-adjusted 2022 USD), $proficiency_i$ is the test score of individual *i*, use_i is the index of skills use at work, X_i' is a vector of controls (including gender, immigration background, age, age squared, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment), and ε_i is the error term. To make coefficients directly comparable, wages are regressed on one standard deviation increase in both $proficiency_i$ and use_i.[1] To check whether the effects of proficiency and use are statistically different from each other, a Wald test of the following linear hypothesis is then performed:

$$H_0 \colon \beta_{proficiency} = \gamma_{use}$$

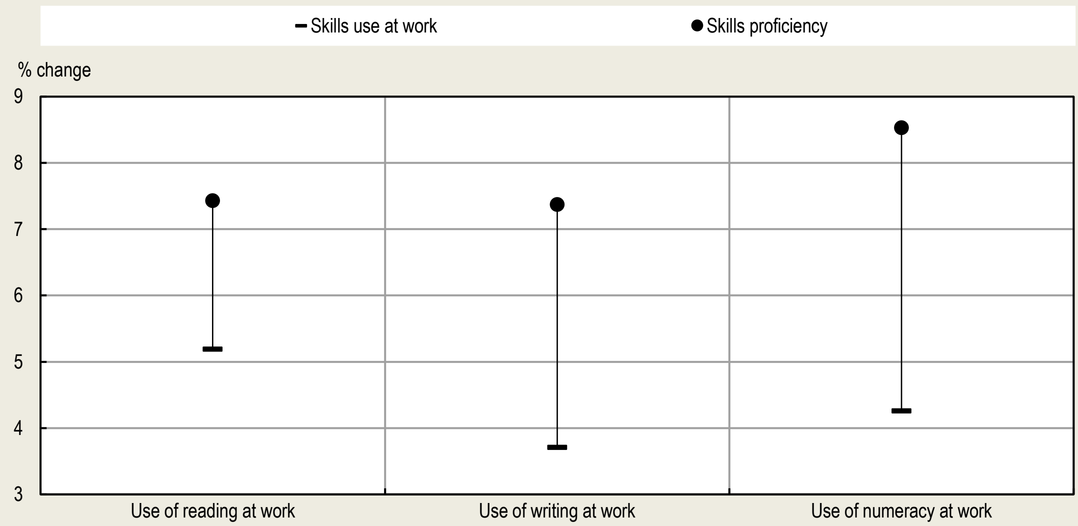
Equation 2.2.

Figure 2.2 shows that proficiency has a consistently stronger impact on wages than use. For example, a one-standard-deviation increase in literacy proficiency is associated with an average wage increase of 7%, compared with a 5% increase for reading use at work. According to the Wald test, these coefficients differ significantly, which implies that proficiency and use make distinct contributions to wages. A similar pattern emerges for writing, where proficiency carries a larger premium than use. The divergence is most pronounced for numeracy: proficiency in numeracy yields an 8.5% wage premium, double the 4.3% associated with numeracy use at work.

Several explanations may help account for this gap. First, proficiency reflects the underlying stock of cognitive skills that individuals can draw upon across a wide range of tasks and contexts, including those not explicitly captured by self-reported skills use. Employers may reward proficiency more strongly because it signals adaptability and learning potential, which are critical in dynamic labour markets. Second, use at work is partly determined by job design and task allocation, which may not fully exploit an individual’s abilities. Workers with high proficiency but limited opportunities to apply these skills may still secure higher wages, particularly if proficiency is recognised by credentials or through occupational sorting. Finally, wage-setting institutions may attach higher value to proficiency because it aligns with formal qualifications and educational attainment, which are often central to pay scales and career progression.

Figure 2.2. Wage returns to skills proficiency and skills use

Association between a one-standard-deviation increase and hourly wages, OLS coefficients



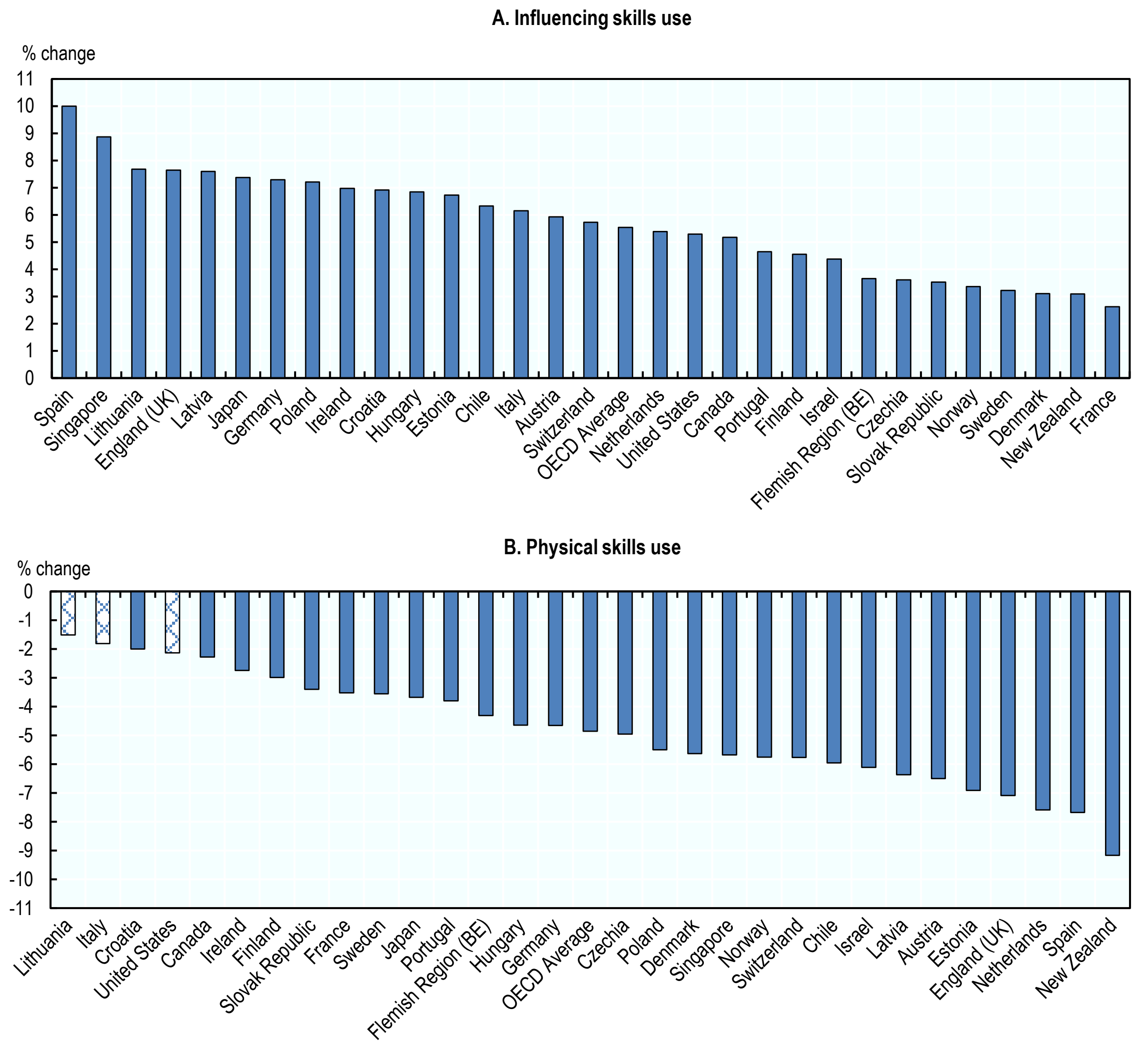
Note:
1. Standardising both proficiency and skill-use variables allows coefficients to be expressed on a comparable scale, but this approach has limitations, as the standard deviation of a frequency-based skill-use index may not represent an equivalent "distance" or effort as a one-standard-deviation increase in proficiency scores. Hence, while standardisation facilitates comparison, it should not be interpreted as implying equivalence in what it means to move one standard deviation along each dimension.
The Figure represents the coefficient of OLS regressions of skills use and proficiency on wages, weighted by sampling weights. Wages are gross hourly earnings for employed and self-employed individuals, including bonuses, in PPP-adjusted 2022 USD. The wage distribution was trimmed to eliminate the 1st and 99th percentiles. The sample includes only full-time workers aged 25-65. One model is estimated for each skill, with the corresponding skills use and proficiency as independent variables (literacy scores for reading and writing use at work, and numeracy scores for numeracy use at work). Coefficients are adjusted for gender, immigration background, age, age squared, whether one lives with a partner or has children, educational attainment, occupation, industry, firm size, permanent contract, public employment, and country fixed effects. All coefficients are statistically significant (at least at the 10% significance level). Korea is not included in the analysis due to unusual response patterns on wages.
Source: 2023 Survey of Adult Skills.

Looking only at cross-country averages, however, masks substantial variation in the wage returns to skills use. Figure 2.3 illustrates this point by comparing the association between wages and the use of those skills that on average show the largest and smallest association with wages – i.e. influencing skills and physical skills – across countries. The relationship between the use of influencing skills and wages is positive everywhere, but their magnitude differs sharply. In Spain, workers who use influencing skills more intensively earn wages that are 10% higher, while in France the difference in wages is just over 2%. Such variation suggests that institutional arrangements and the demand for influencing skills differ significantly between labour markets.

In contrast, returns to physical skills are consistently negative throughout the sample, but again there are notable cross-country differences. In New Zealand and Spain, intensive use of physical skills is associated with an earnings penalty of more than 9%, whereas in Lithuania and Italy the effect is close to zero and not statistically significant. These results likely reflect technological intensity and wage-setting systems. In countries where manufacturing, agriculture or manual services still represent a significant share of employment, the wage penalty seems to be less pronounced.

Figure 2.3. Wage returns to selected skills use by country

Association of a one-standard-deviation increase in the use of each skill and hourly wages, OLS coefficients



Note: The Figure represents the coefficients of OLS regressions of skills use on wages, weighted by sampling weights. Each bar represents a separate regression. Wages are gross hourly earnings for employed and self-employed individuals, including bonuses, in PPP-adjusted 2022 USD. The wage distribution was trimmed to eliminate the 1st and 99th percentiles. The sample includes only full-time workers aged 25-65. Coefficients are adjusted for gender, immigration background, age, age squared, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, and public employment. Bars with a checkered pattern are not statistically significant (at the 10% significance level).
Source: 2023 Survey of Adult Skills.

Returns to skills use may also vary between socio-demographic groups. Understanding whether the association between skills use and wages differs between groups is important for at least two reasons. First, it sheds light on whether skills are valued differently in the labour market depending on who uses them, which speaks directly to issues of equity and discrimination. Second, it allows for a better understanding of the mechanisms underlying the pay gaps. For instance, if women receive lower returns to the same skills use levels, the gap cannot be explained solely by differences in skills use, skill proficiency or occupational choices, but also by how labour markets reward skills use.

Table 2.1 presents estimates of wage returns to skills use, and includes an interaction term that indicates whether returns differ for men and women. The results show that most skills (except manual and physical ones) are associated with higher wages when used more frequently (column 1). The interaction term in column 3 is generally not statistically significant for many skills, which suggests that, in most cases, men and women obtain similar returns once they use a given skill with the same frequency. Using PIAAC data, Battisti, Fedorets and Kinne (2023[7]) find similar non-significant results when looking at the impact of the interaction term between a female dummy and numeracy proficiency on wages.

However, Table 2.1 also shows a few important exceptions. For learning at work and self-organising skills, the interaction coefficients are positive and significant, indicating that women receive higher wage returns than men for the use of these skills at work. Women who report no use of self-organising skills at work earn on average 14% less than men. Yet when these skills are more intensively utilised, the wage gradient is steeper for women. A one-standard-deviation increase in their use corresponds to 2% higher wages for men and 5% higher wages for women, implying that greater opportunities for self-management could reduce or even reverse the gender pay gap.

The overall message is therefore twofold. On the one hand, women face a systematic wage disadvantage across the board, as shown by the large and negative baseline coefficients for women in column 2 (which is in line with much of the literature exploiting PIAAC data to estimate the gender wage gap, such as Christl and Köppl – Turyna (2020[8]), Rebollo-Sanz and De la Rica (2022[9]) and Komatsu (2023[10])). On the other hand, the interaction terms show that for a limited set of skills uses – particularly learning at work and self-organisation – the returns are somewhat more favourable to women compared to men. These patterns may reflect the fact that either women have specific non-observable characteristics that are rewarded differently, or employers perceive that skills use by women in these areas is especially valuable. It may also reflect occupational segregation: women who succeed in highly autonomous jobs may occupy positions where they are positively discriminated, resulting in higher relative rewards.

Table 2.1. Gender differences in wage returns to skills use

Association between a one-standard-deviation increase in the use of each skill and hourly wages, OLS coefficients

	(1) Skills use	(2) Women	(3) Women * Skills use
Reading	0.0521***	-0.133***	-0.0004
Writing	0.0325***	-0.141***	0.0107
Numeracy	0.0442***	-0.132***	0.0067
ICT	0.0413***	-0.135***	0.0166
Problem solving	0.0429***	-0.139***	0.0048
Task discretion	0.0437***	-0.143***	-0.0039
Learning at work	0.0091	-0.146***	0.0259**
Influencing	0.0606***	-0.135***	0.0083
Co-operative skills	0.0094	-0.146***	0.0048
Self-organising skills	0.0224***	-0.141***	0.0246**
Dexterity	-0.0293***	-0.143***	0.0007
Physical skills	-0.0470***	-0.149***	0.0126

Note: Each row represents a separate regression. Controls are not shown, but include immigration background, age, age squared, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment, and country fixed effects. The interaction term highlights whether part of the wage gap is due to differences in how skills use is valued for men versus women. If the interaction coefficient is significant and negative (positive), it suggests that women earn less (more) than men for the same level of skills use, while if it is not significant, the return to skills use is the same for both genders. Korea is not included in the analysis due to unusual response patterns on wages.
Source: 2023 Survey of Adult Skills.

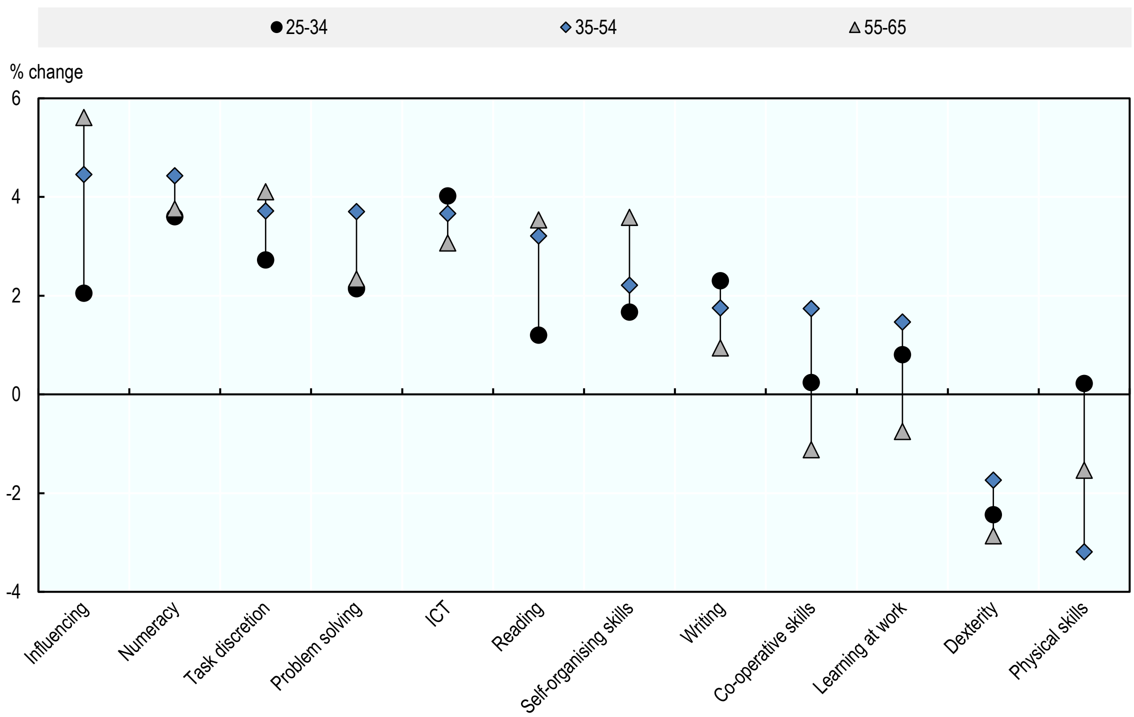
Similarly, analysing the association of wages with skills use by age group provides important insights into how skills use is valued at different stages of a worker's career. Age not only reflects accumulated work experience but also shapes occupational positions, task allocations and opportunities to apply skills. Younger workers may be in jobs that reward skills use differently than older workers, either because they are still in career-building stages, because they are concentrated in entry-level positions with limited bargaining power, or because employers perceive their skills use as a signal of potential. Younger and older workers may be in occupations where skills use is rewarded differently depending on whether it complements or substitutes for experience, and whether it is aligned with evolving technological and organisational demands. Disaggregating the relationship by age therefore helps identify whether labour markets reward skills use consistently throughout the life cycle or whether wages and skills use interacts with career trajectories and institutional arrangements in distinctive ways.

Figure 2.4 presents the association between wages and skills use separately for three age groups. Two patterns stand out. First, across several skill domains (and especially for influencing and reading skills), younger workers aged 25 to 34 receive lower wage premia for skills use than mid-career and older workers. This is consistent with labour markets in which responsibility and pay rise with tenure, so the same skill used by a junior employee affects less strategic decisions and generates less "measurable" value. Selection and survivorship mechanisms could reinforce the pattern, since those who remain in roles that intensively use these skills may tend to be the workers for whom the market pays higher premia.

Second, older workers either see the highest or the lowest wage association with skills use depending on the skill considered. For instance, influencing skills, task discretion and self-organising skills are associated with the highest wages for workers aged 55 to 65. By contrast, for skills such as learning at work, co-operative skills and dexterity, older workers receive the lowest premia, with coefficients that are negative. This polarisation may reflect the dual role of age in the labour market. On the one hand, experience and tenure may amplify the value of certain high-level skills that build on authority and autonomy. On the other hand, older workers may face occupational constraints in domains where physical skills are critical, which reduce or even reverse the wage premium associated with using these skills.

Figure 2.4. Wage returns to skills use by age group

Association between a one-standard-deviation increase in the use of each skill and hourly wages, OLS coefficients



Note: The Figure represents the coefficients of OLS regressions of skills use on wages, weighted by sampling weights. Each marker represents a separate regression. Wages are gross hourly earnings for employed and self-employed individuals, including bonuses, in PPP-adjusted 2022 USD. The wage distribution was trimmed to eliminate the 1st and 99th percentiles. The sample includes only full-time workers aged 25-65. Coefficients are adjusted for gender, immigration background, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment, and country fixed effects. Korea is not included in the analysis due to unusual response patterns on wages.
Source: 2023 Survey of Adult Skills.

The broader links between skills use at work, inequality and productivity

The evidence so far suggests that inequalities in how workers are able to apply their skills on the job reinforce disparities in pay arising from different skill levels, as workers with greater opportunities to deploy skills may command wage premiums, while those in roles with limited skills use remain in lower pay brackets. Unequal skills use may also reflect discriminatory managerial practices, which can exacerbate inequalities in pay.

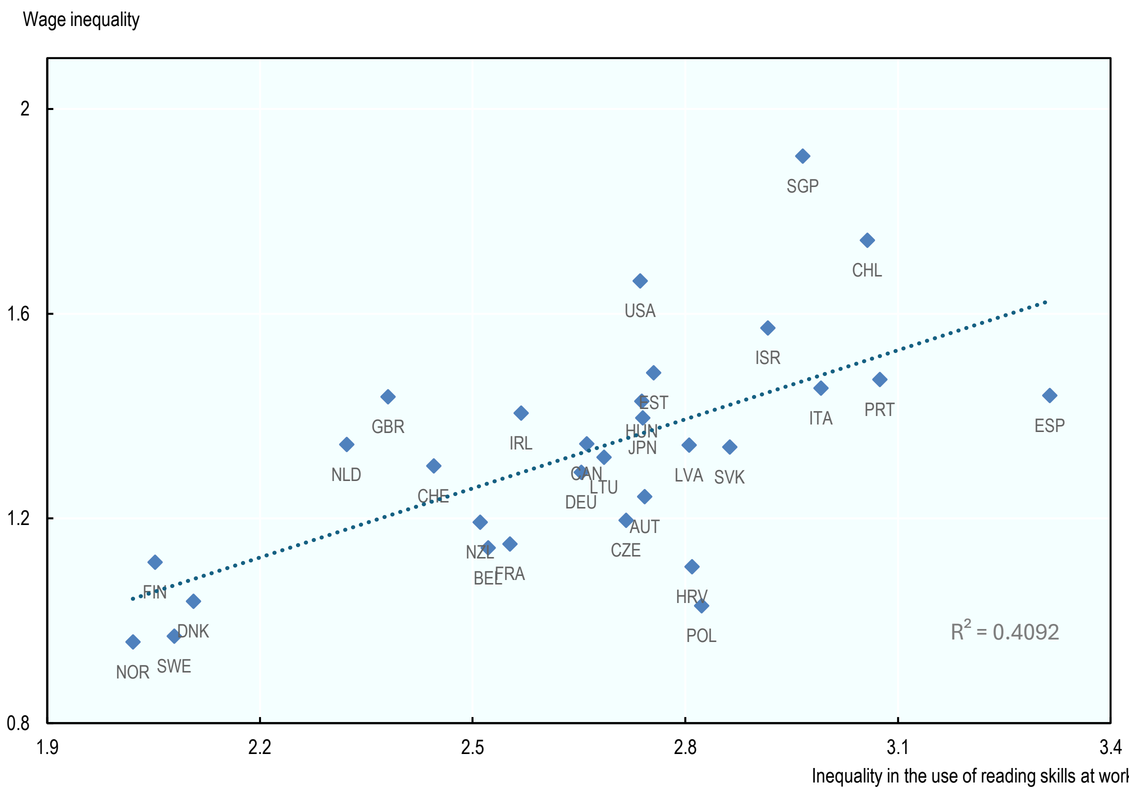
Understanding the broader relationship between skills and wage inequality has been a central theme in recent labour economics, but the debate has largely focussed on proficiency rather than the use of skills at work. For instance, using data from the first cycle of PIAAC, Paccagnella (2015[11]) finds that while proficiency in cognitive skills is associated with positive wage returns, the correlation between the dispersion of proficiency and the dispersion of wages across countries is weak, and in some cases even negative. This perspective is reinforced by Broecke, Quintini and Vandeweyer (2019[12]), which emphasised how differences in wage inequality across countries are driven primarily by differences in the return to skills and by how well the supply of skills meets the demand.

However, the existing literature has not fully leveraged the information on how skills are used in the workplace, even though this margin may be critical in shaping how proficiency translates into wage outcomes. Indeed, skills use provides a way of observing the match between workers' capacities and the frequency of their use at work, which mediates the transmission of proficiency into wages. Only OECD (2015[13]) exploited information on skills use at work to simulate the impact that improving numeracy skills use would have on wage inequality. They find that in most of the countries included in the first cycle of the Survey of Adult Skills, wage inequality measured by the Gini coefficient would indeed decline if numeracy skills were more frequently used in the labour market.

Exploiting the new cycle of PIAAC data, Figure 2.5 plots the relationship between wage inequality and inequality in the use of reading skills at work, using the gap between the 90th and 10th percentiles of both distributions.[3] The positive slope of the fitted regression suggests that countries where the use of reading skills is more unequally distributed among workers also tend to display higher levels of wage inequality. The explanatory power of this relationship is non-trivial, with an R-squared of 0.41, suggesting that about 40% of the cross-country variation in wage inequality can be accounted for by inequality in skills use.[4] While the relationship is purely descriptive and does not account for other structural factors that may also influence wage dispersion, the findings still underscore the importance of considering not only the availability of skills in the workforce but also how they are used at work as a determinant of wage dispersion.

Nordic countries such as Norway, Sweden, Denmark, and Finland cluster in the lower-left corner of the graph, combining both relatively equal skills use and low wage inequality. This reflects their institutional settings, with compressed wage structures (Mogstad, Salvanes and Torsvik, 2025[14]) and workplace practices that distribute skill-intensive tasks more evenly between similar workers and jobs. At the other extreme, countries like Spain and Chile appear in the upper-right corner, where both skill-use inequality and wage inequality are high, consistent with labour markets characterised by dual structures and segmented opportunities for high- versus low-skill tasks. Anglo-Saxon countries such as the United States, Canada and the United Kingdom fall in the mid-range of both wage inequality and skills-use inequality, suggesting that other unobserved institutional factors – such as weak collective bargaining or high returns to top-end occupations – are also at play.

Figure 2.5. Wage inequality and inequality in the use of reading skills at work

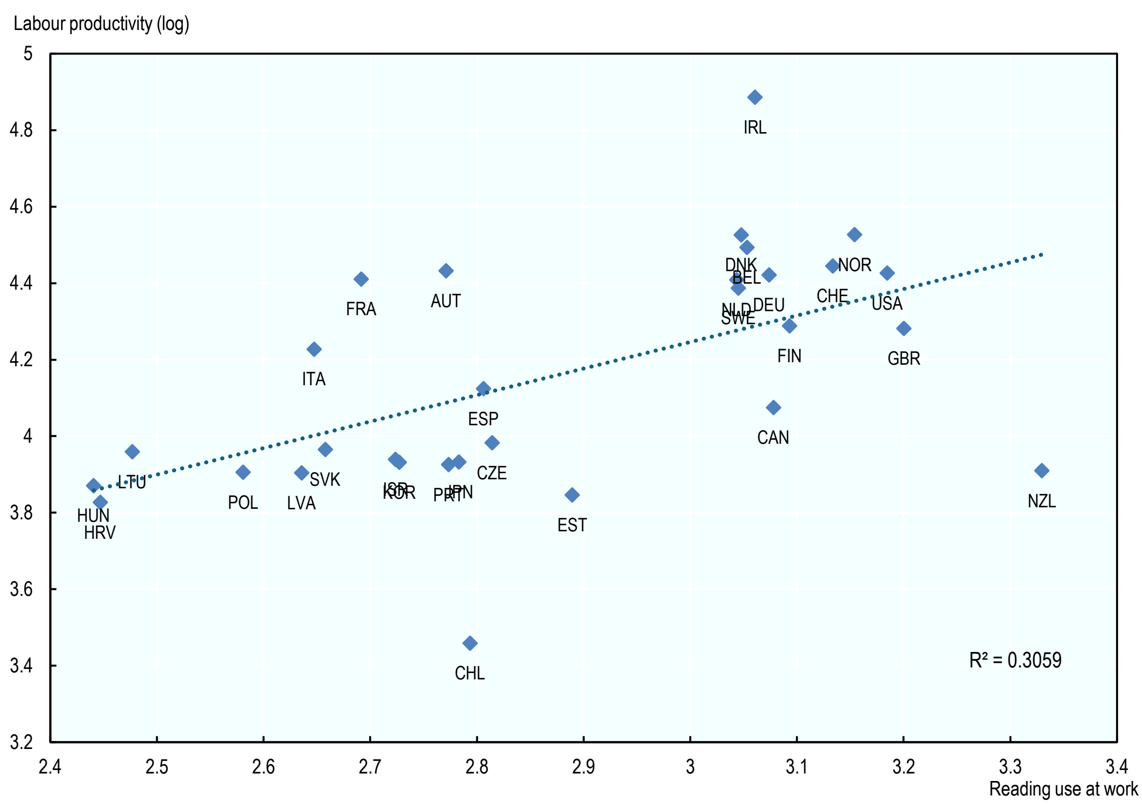


Note: Wage inequality is measured as the difference between the top and the bottom deciles of the (log) wage distribution. Wages are gross hourly earnings for employed and self-employed individuals, including bonuses, in PPP-adjusted 2022 USD. The wage distribution was trimmed to eliminate the 1st and 99th percentiles. Similarly, inequality in the use of reading skills at work is calculated as the difference between the top and bottom deciles of the skills use distribution. The sample includes only full-time workers aged 25-65. For consistency, the country name is reported for Belgium and the United Kingdom, even if the Survey of Adult Skills is conducted only at subnational level – namely in the Flemish region and in England, respectively. Korea is not included in the analysis due to unusual response patterns on wages.
Source: 2023 Survey of Adult Skills.

The efficiency with which skills are used in different jobs and firms is also associated with cross-country differences in labour productivity. Adalet McGowan and Andrews (2017[15]) show that when the skills workers possess are misaligned with the requirements of their jobs – whether through over-skilling or under-qualification – aggregate labour productivity is lower. Their cross-country, industry-level estimates attribute the drag primarily to two margins: a loss of allocative efficiency as high-productivity firms are less able to attract appropriately skilled workers (a between-firm reallocation failure), and a within-firm shortfall where under-qualified workers depress establishment-level productivity. Exploiting 2023 Survey of Adult Skills data, Andrews, Égert and de la Maisonneuve (2025[16]) document a strong positive association between the average level of adult skills and industry labour productivity across countries. Crucially, they also show that allocation matters independently of average skill: industries with lower labour-market mismatch and with a higher propensity for high-skilled workers to be employed in larger, more dynamic firms exhibit higher productivity.

Figure 2.6 illustrates the cross-country relationship between labour productivity and the frequency of reading skills at work. The positive slope of the regression line indicates that economies where workers more frequently use reading skills at work tend to achieve higher levels of GDP per hour worked, with the estimated correlation ($R^2 \approx 0.31$) suggesting that skills use explains a non-trivial share of the variation in productivity across OECD countries.[5] High-productivity economies such as Ireland, Norway, Switzerland and the United States combine above-average productivity with high reported use of reading skills. By contrast, countries in Central and Eastern Europe (e.g. Hungary, Lithuania, Croatia) cluster at the lower end of both productivity and skills use, reinforcing the view that insufficient utilisation of available skills constrains aggregate performance. Some outliers such as New Zealand – high reading skills use but relatively modest productivity – or Chile – low productivity despite average skills use – highlight that while the skills-use channel is important, other structural factors including capital deepening, industry mix and institutional quality are at play.

Figure 2.6. Labour productivity and reading skills use in the workplace



Note: Labour productivity is expressed as the natural logarithm of GDP per hour worked in PPP-adjusted 2020 USD. For consistency, the country name is reported for Belgium and the United Kingdom, even if the Survey of Adult Skills is conducted only at subnational level – namely in the Flemish region and in England, respectively.
Source: 2023 Survey of Adult Skills; OECD Productivity Database (2023).

Skills use and worker well-being

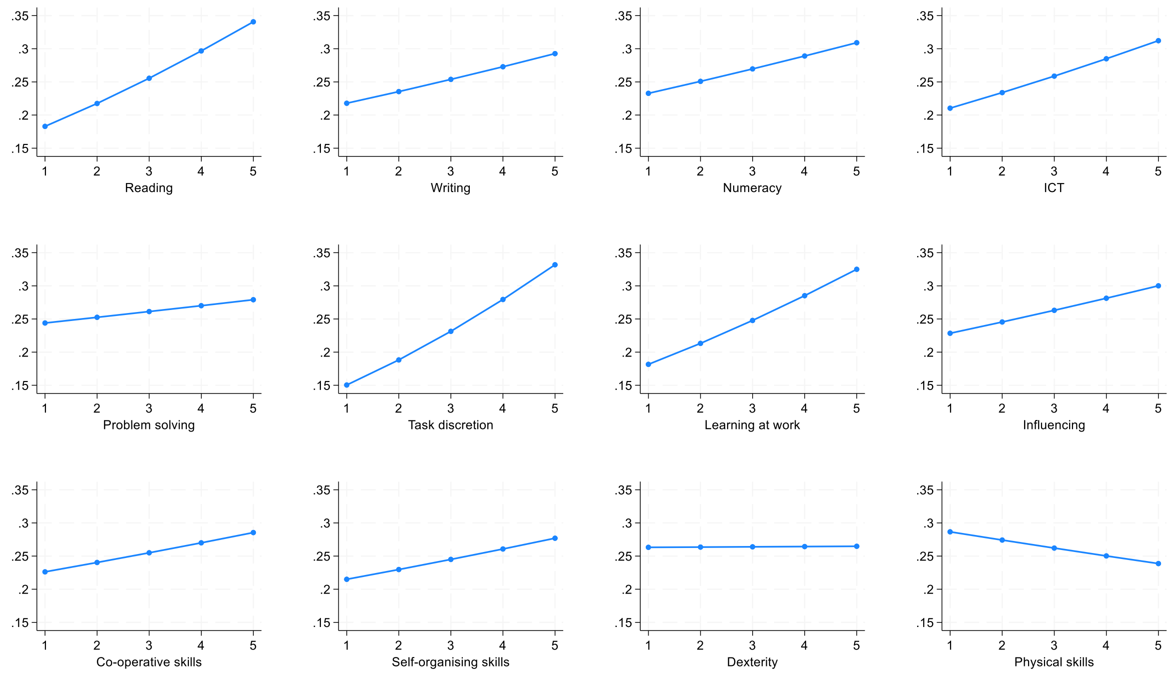
At its core, skills use captures whether job design and production technologies actually allow workers to use the skills they possess – what scholars often call skill discretion or skill utilisation (Fujishiro and Heaney, 2017[17]). When workers are placed in roles where their skills are better used, the job generates intrinsic motivation and satisfaction; when they are not, the job becomes a source of disutility, increasing the risk of turnover (Dopeso-Fernández, Giusti and Kucel, 2023[18]).[6] For example, Boxall, Hutchison, and Wassenaar (2015[19]) show that high-involvement work processes (discretion, participation, developmental practices) improve employee outcomes not merely through direct effects but because they raise skills use and intrinsic motivation, thereby improving job satisfaction and well-being. The returns to skills use seem to extend even beyond the workplace. Fujishiro and Heaney (2017[17]) document that higher skills use – operationalised as "doing what I do best" – is associated with better self-rated physical health, with part of the effect mediated by healthier behaviours.

Figure 2.7 shows the marginal probability of being extremely satisfied at work as a function of skills use, using data from the 2023 Survey of Adult Skills. Coefficients are adjusted for gender, immigration background, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment, wages and country fixed effects. A consistent pattern emerges across most domains: higher frequency of skills use – whether in information-processing or generic skills – is positively and significantly associated with the probability of reporting the highest level of job satisfaction. The positive relationships are not trivial in magnitude. For example, the predicted probability of being extremely satisfied almost doubles between the lowest and highest levels of use of learning-at-work skills, underscoring the importance of learning opportunities and continuous skill engagement as key determinants of job satisfaction.[7] The use of task discretion at work is also strongly associated with job satisfaction. This should come as no surprise since task discretion connects directly to the dimension of autonomy, a core component of self-determination theory: having control over how tasks are performed allows workers to align work processes with their own problem-solving styles, pace, and preferences, effectively increasing the "consumption value" of the job (Hackman and Oldham, 1976[20]). It also signals trust from employers, reducing perceived monitoring costs and fostering organisational commitment.

By contrast, dexterity use at work exhibits a notably flat relationship with job satisfaction, suggesting that manual precision tasks – unlike cognitive or autonomy-related skills – do not generate the same intrinsic motivational returns. The use of physical skills displays a slightly negative slope, indicating that jobs requiring more physically demanding tasks are associated with lower likelihoods of being extremely satisfied, all else (including wages) equal. This pattern is consistent with the idea that, while greater skills use generally entails effort costs, those associated with cognitive skills tend to be offset by intrinsic rewards (such as autonomy or pro-social preferences), whereas the disutility from physically strenuous work appears less compensated. Box 2.2 shows similar results for the relationship between skills use at work and life satisfaction.

Figure 2.7. Job satisfaction and skills use

Marginal probability change of being extremely satisfied at work



Note: The Figure displays the predicted probability of being extremely satisfied at work (job satisfaction equal to 5 in a 1-5 scale) by skills use in the workplace, based on a weighted regression model. Each graph represents a separate regression. The sample includes only full-time workers aged 25-65. Coefficients are adjusted for gender, immigration background, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment, wages and country fixed effects. All coefficients are statistically significant (at the 1% significance level).
Source: 2023 Survey of Adult Skills.

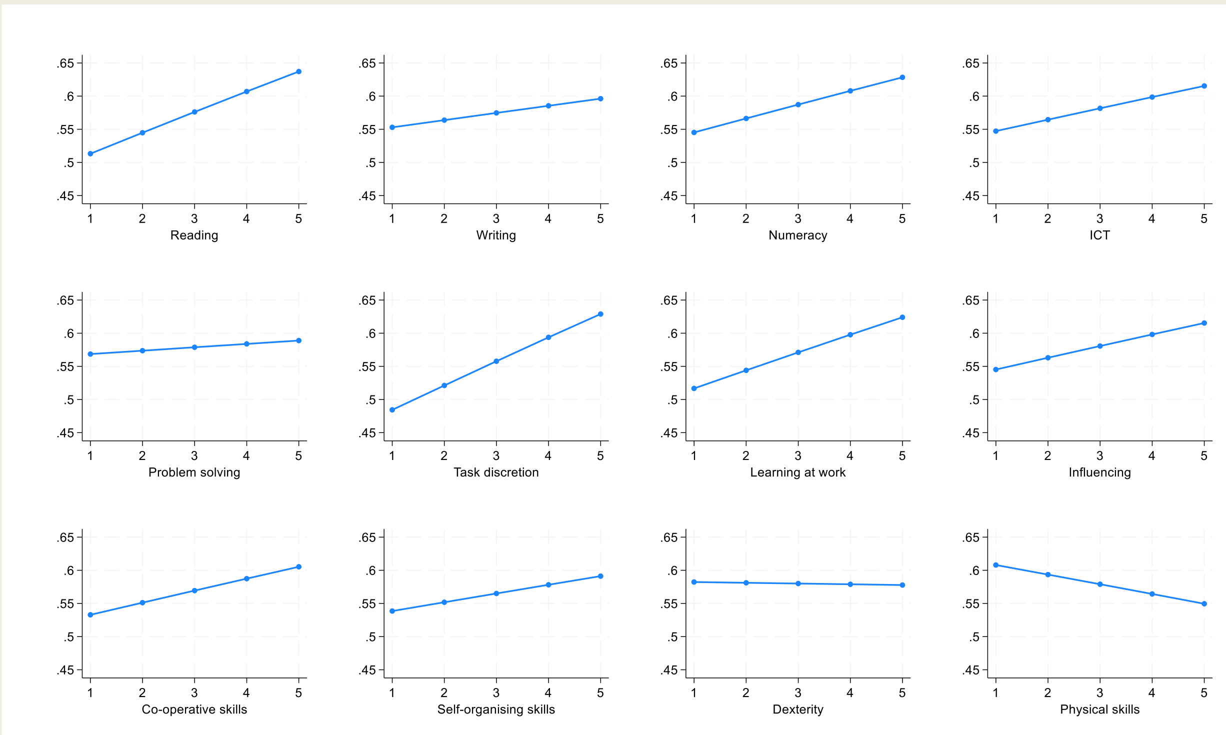
Box 2.2. The spillover impact of skills use at work on life satisfaction

Although the relationship between the deployment of skills at work and overall life satisfaction is unlikely to be entirely direct, as it may operate through intermediate channels such as job satisfaction, it remains valuable to investigate whether skills use is correlated with life satisfaction, since this would suggest that the effects of workplace experiences extend beyond the professional domain. The application of skills can reinforce a sense of competence, personal development and autonomy, all of which are dimensions that contribute to subjective well-being. If individuals derive fulfilment from exercising and expanding their capabilities, the benefits may spill over into their broader quality of life, shaping perceptions of purpose and achievement outside the workplace.

Figure 2.8 illustrates the estimated marginal effects of skills use at work on the probability of reporting extremely high life satisfaction. Similarly to the previous analysis on job satisfaction, the results indicate that greater use of skills in the workplace is associated with higher life satisfaction across almost all domains. These findings are robust to adjustments for gender, immigration background, family composition, education, wages, occupation, industry and employment conditions, which implies that the associations are not merely capturing compositional differences in the workforce. Taken together with the findings on job satisfaction, the evidence highlights that not all skills are equally relevant for job and life satisfaction, and that opportunities for cognitive challenge and decision making at work may be especially valuable for well-being outcomes.

Figure 2.8. Life satisfaction and skills use

Marginal probability change of being extremely satisfied in life



Note: The Figure displays the predicted probability of being extremely satisfied in life (life satisfaction equal to 9 or 10 in a 1-10 scale) by skills use in the workplace, based on a weighted regression model. Each graph represents a separate regression. The sample includes only full-time workers aged 25-65. Coefficients are adjusted for gender, immigration background, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment, wages and country fixed effects. All coefficients are statistically significant (at the 1% significance level).
Source: 2023 Survey of Adult Skills.

Another risk to job quality and worker well-being that has so far been overlooked in the economic literature on the returns to skills and skills use is job burnout. Burnout represents a critical outcome to consider, as it reflects the potential costs of skills use when demands become excessive or when workers face persistent mismatches between their abilities and the conditions under which they are deployed. The relative scarcity of high-quality data on mental health and psychosocial risks in the workplace means that this aspect is often ignored.

Burnout (as defined by World Health Organization) involves emotional exhaustion, cynicism (feeling detached from or negative toward one's job), and reduced professional efficacy.[8] While the Survey of Adult Skills does not include standardised burnout inventories like the Maslach Burnout Inventory or Copenhagen Burnout Inventory (see Romo et al. (2025[21]) for a technical discuss of the existing burnout diagnostic tools), it is possible to create a proxy measure of burnout risk. In particular, a composite Burnout Risk Index can be computed aggregating together the following PIAAC variables:[9]

- Exhaustion: pace of work, frequency of working to tight deadlines.
- Cynicism: self-reported job satisfaction, tendency to feel depressed.
- Reduced efficacy: perceived over-skilling, perceived overqualification.

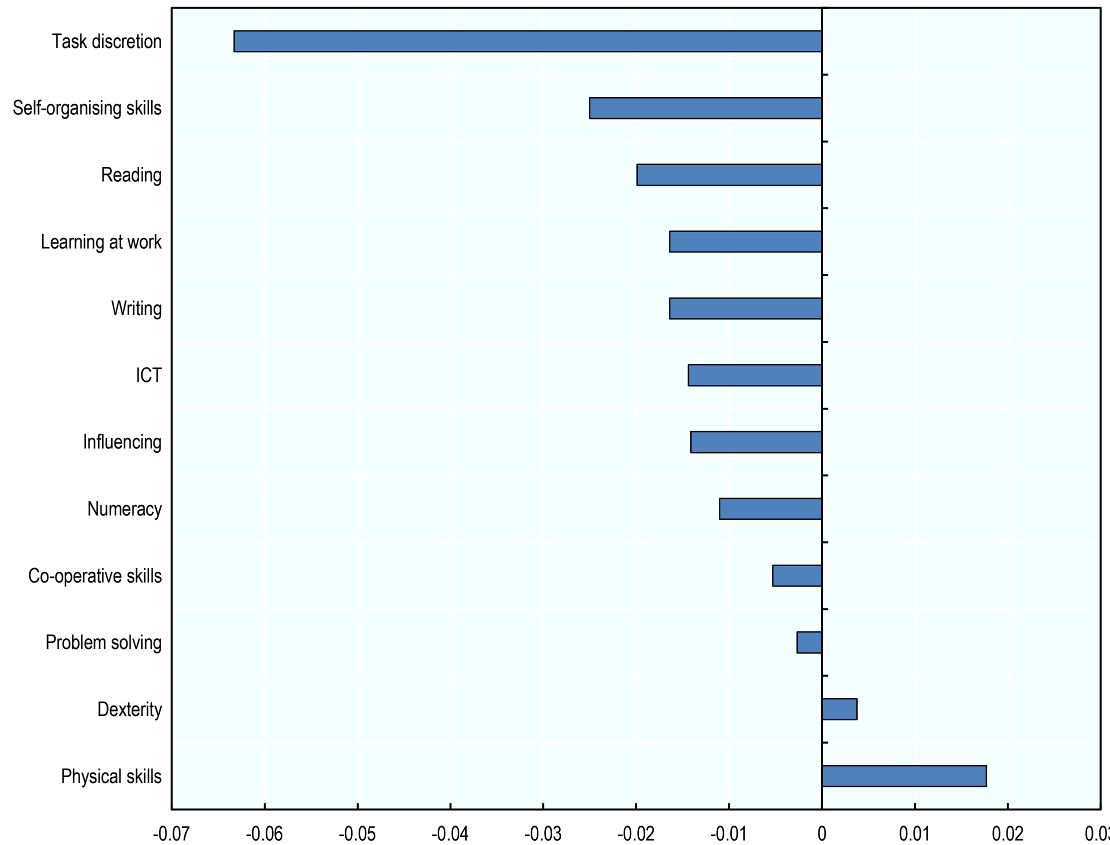
These six variables are combined using factor analysis, a statistical method that identifies the common latent structure underlying a set of observed indicators and assigns weights according to the contribution of each variable to the extracted factor. The scores have been rescaled to range between 0 and 1 (using a min-max approach) in order to facilitate interpretation and comparability across units of analysis (see OECD/European Union/EC-JRC (2008[22]) for more details on the construction of composite indices). Clearly, any interpretation should be cautious, as this composite index is about risk factors and not actual burnout prevalence.

Figure 2.9 presents the estimated effects of the use of different skills at work on the Burnout Risk Index. The results show that, after controlling for individual and job characteristics, greater task discretion and the use of self-organising skills are strongly associated with a lower risk of burnout. In both cases the coefficients are negative and highly significant, with task discretion displaying the largest negative effect. This confirms the previous finding in this chapter that workers who have more autonomy in how they perform their tasks, and who rely on organisational skills to manage their workload are more likely to be satisfied at work. Reading, learning at work and writing also exhibit negative and significant coefficients, although the magnitude of these effects is smaller.

By contrast, the use of physical skills shows a positive association with burnout risk, with the coefficient being both statistically significant and relatively large. This indicates that occupations requiring a high degree of physical effort may contribute to higher levels of burnout, possibly due to physical strain, lower job satisfaction or the limited scope for autonomy in such roles. Dexterity and problem-solving skills display weaker and less consistent effects, with coefficients close to zero, while the use of numeracy, ICT, influencing, and co-operative skills is associated with only modest reductions in burnout risk.

Figure 2.9. Risk of job burnout and the use of skills at work

Effect of a one-standard-deviation increase on Burnout Risk Index



Note: The Figure represents the coefficients of OLS regressions of skills use on the Burnout Risk Index, weighted by sampling weights. Each bar represents a separate regression. The sample includes only full-time workers aged 25-65. Coefficients are adjusted for gender, immigration background, age, age squared, whether one lives with a partner or has children, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment, and country fixed effects. All coefficients are statistically significant (at the 1% significance level).
Source: 2023 Survey of Adult Skills.

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Notes

[1] Similarly to OECD (2024[23]), wages are measured as log hourly earnings for employed and self-employed individuals, including bonuses, expressed in PPP-adjusted 2022 USD.

[2] Although much of the economic literature (for example, Hanushek et al. (2015[24]) and Falck, Heimisch-Roecker and Wiederhold (2021[25])), often refers to these associations as "returns to skills use", this is not

a rate of return in the strict sense, as it does not incorporate the costs of attaining a given level of skills use.

[3] Results are confirmed looking at the association between wage inequality and inequality in the use of the other information-processing and generic skills computed in this report.

[4] Note that an even slightly higher R-squared ($R^2 \approx 0.54$) is found when estimates are adjusted by including a control for inequality in literacy proficiency score.

[5] In line with the findings of OECD (2013[26]), an even larger R-squared ($R^2 \approx 0.39$) is found when controlling for literacy proficiency score.

[6] Intrinsic motivation refers to an agent's engagement in an activity for its own sake – driven by the inherent interest or moral satisfaction associated with the task – whereas extrinsic motivation refers to incentives external to the agent (such as monetary rewards, punishments, or monitoring) (Bénabou and Tirole, 2003[27]).

[7] It should also be noted that the association may operate in both directions, as individuals who are satisfied in their jobs may also be more inclined to seek additional learning and development opportunities.

[8] The 11th Revision of the International Classification of Diseases (ICD-11) of the World Health Organization (WHO) defines burnout as "a syndrome conceptualized as resulting from chronic workplace stress that has not been successfully managed. It is characterized by three dimensions: feelings of energy depletion or exhaustion; increased mental distance from one's job, or feelings of negativism or cynicism related to one's job; and reduced professional efficacy. Burn-out refers specifically to phenomena in the occupational context and should not be applied to describe experiences in other areas of life." See here: https://www.who.int/standards/classifications/frequently-asked-questions/burn-out-an-occupational-phenomenon (accessed on 26 November 2025).

[9] More specifically, the Cycle 2 PIAAC variables used in the Burnout Risk Index are the following: (1) H2_Q08c "To what extent could you choose or change the speed or rate at which you work?"; (2) H2_Q12 "How often does your current job usually involve working to tight deadlines or at very high speed?"; (3) D2_Q13 "All things considered, how satisfied are you with your current work?"; (4) K2_Q02d "Indicate the extent to which you agree or disagree with the statement 'I tend to feel depressed, blue'"; (5) H2_Q19a "Overall, which of the following statements best describes your skills in relation to what is required to do your job?"; and (6) D2_Q12a "If applying today, what would be the usual qualification, if any, that someone would need to get this type of job?". In particular, over-qualification and over-skilling are included as components of reduced professional efficacy because, when individuals perceive that their skills or qualifications exceed those required by their job, they are more likely to experience under-utilisation, lack of challenge, and diminished sense of purpose or accomplishment at work.

3 How has skills use changed over time

The 2023 Survey of Adult Skills enables, for the first time, an analysis of how skills-use has evolved over time. This chapter examines how the use of information-processing and generic skills in the workplace has changed over the past decade, and how these patterns differ between countries and occupations. The analysis pays particular attention to two groups traditionally lagging behind in skills use – low-qualified workers and women – assessing whether they have caught up over the past decade. Understanding these dynamics is essential not only for advancing equity in the labour market but also for ensuring that available talent is fully utilised.

In Brief

The evolution of skills use at work is highly heterogenous

- Over the past decade, the use of information-processing skills has increased markedly and consistently across countries, while the use of generic skills has remained broadly stable. The use of reading, writing, numeracy, ICT and problem-solving skills has expanded significantly, with particularly strong gains in writing and ICT use. By contrast, the use of task discretion, learning at work, influencing and co-operative skills has changed little over time on average, with significant differences in the change across countries.
- ICT use has risen especially among workers in low- and medium-skilled occupations, indicating that digital demands are now pervasive across the labour market. In contrast, the use of physical and dexterity skills has declined, pointing to a continued shift towards the automation of physical tasks.
- The use of skills at work has increased substantially among low-qualified adults, narrowing the gap with higher-qualified workers in most domains, particularly in numeracy, ICT and influencing skills. This convergence is driven mainly by within-occupation increases in the use of these skills rather than changes in the distribution of low-qualified by occupation, suggesting that job upgrading and greater skills use are occurring across the qualification spectrum.
- There is limited evidence of overall convergence between men and women in the use of skills at work over the past decade. Some progress is observed in the use of co-operative skills, yet declines in domains such as numeracy and ICT point to persistent gender disparities. Gender equality in skills use remains closely linked to national labour market structures.

Introduction

Understanding how the use of skills in the workplace evolves over time is essential for assessing how labour markets adapt to technological progress, organisational change and shifting patterns of labour demand. The 2023 Survey of Adult Skills provides, for the first time, comparable measures of skills use collected a decade apart, offering a unique opportunity to analyse how workers' tasks and skill requirements have evolved across countries and occupations. Studying the evolution of skills use is particularly relevant in the context of rapid digitalisation, automation and the diffusion of new forms of work organisation. These forces have transformed not only the composition of employment but also the nature of tasks within occupations, potentially increasing the demand for analytical, digital and collaborative skills while reducing the reliance on routine and physical activities. From a policy perspective, trends in skills use can help identify which groups and sectors are advancing – and which are lagging – to inform strategies to promote inclusive digital transformation, support workplace learning, and strengthen the alignment between skills supply and demand.

The comparison of skills-use measures between the two cycles of the Survey of Adult Skills is made possible by careful survey design, which ensures that results from the second cycle are comparable with those from the first (details on the few methodological differences between the two cycles of the Survey of Adult Skills can be found in Box 3.2 of OECD (2024[1])). In particular, the variables underpinning the indicators of skills use employed in this report show consistency between cycles. Although a limited number of items differ between the questionnaires, considerable effort has been made to maintain continuity in the underlying latent concept of skills use that these variables are intended to capture (OECD, 2021[2]; OECD, 2025[3]). The exact variables used in each cycle to construct the skills use measures of this report are provided in the Annex.[1]

A total of 27 countries and economies participated in both survey cycles. Of the 31 countries and economies included in Cycle 2 and discussed in earlier chapters, only Croatia, Latvia, Portugal and Switzerland did not take part in Cycle 1 and are therefore excluded from the present analysis. For ease of presentation, this report often refers to changes occurring "over the past decade". It should, however, be noted that the first cycle was implemented in three rounds: Round 1 in 2011/12, Round 2 in 2014/15 and Round 3 in 2017. As a result, the time elapsed between the two observations varies across countries. Although the United States was the only country to participate in two rounds of Cycle 1, the analysis of this chapter relies solely on data from Round 1. This choice aligns the US data with the reference period for the majority of the other countries, as 21 countries of the 27 that participated to both cycles also participated in the 2011/12 round.

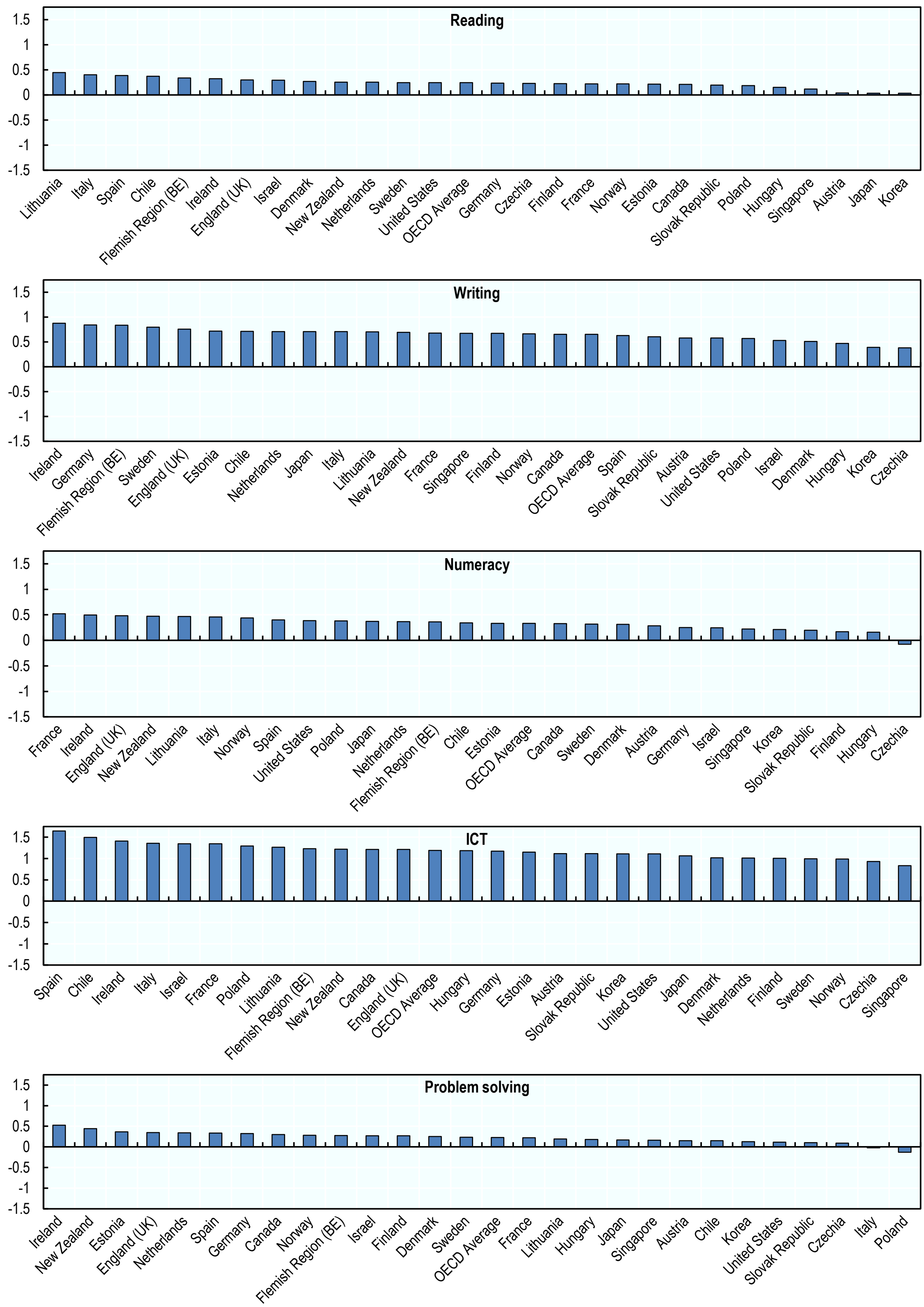
The evolution of the use of skills in the workplace

Figure 3.1 and Figure 3.2 present a comparative overview of changes in the use of information-processing and generic skills at work between the two cycles of the Survey of Adult Skills. The evidence points to a larger and more consistent increase in the use of information-processing skills than in generic skills. The use of generic skills such as task discretion, learning at work, influencing, co-operative skills and physical abilities has on average remained relatively stable over the past decade, with changes typically ranging between -0.5 and +0.5 on the five-point frequency scale.

The evolution of the use of these skills is, however, highly heterogeneous across countries and in several cases the direction of change may be a cause for concern. For example, opportunities for learning at work expanded in Ireland and the Netherlands, yet declined in Italy, the Slovak Republic and Poland. Declines in this area may indicate a weakening of workplace learning systems that are essential for ensuring that workers remain adaptable, particularly in environments undergoing technological or organisational change. Similarly, France and Norway experienced an increase in the use of co-operation skills in the workplace, whereas several Central and Eastern European countries reported reductions. Lower use of co-operative skills may suggest work environments where teamwork and participatory approaches are becoming less central, with potential implications for job quality, but also innovation and firms' performance.

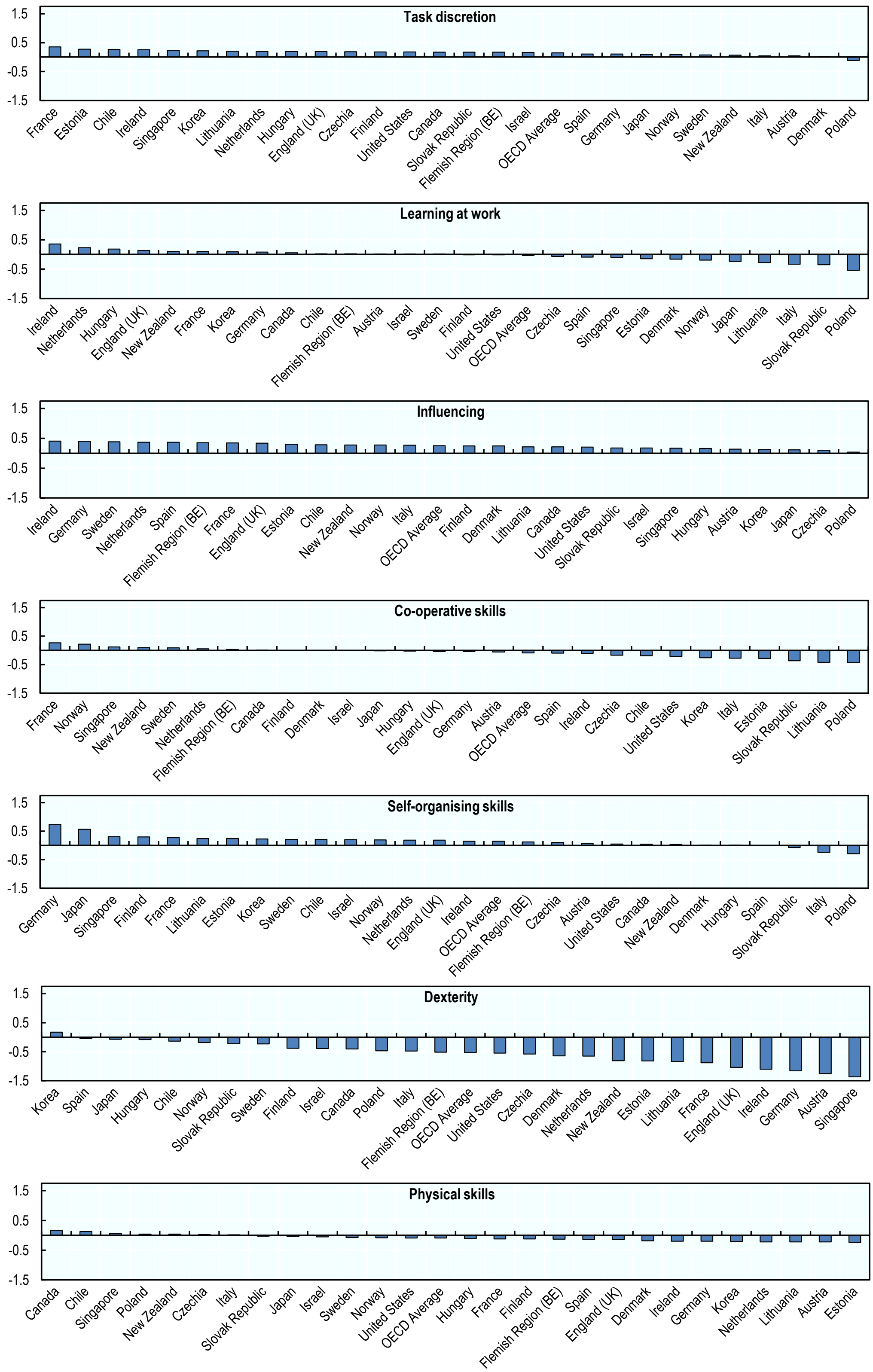
By contrast, the use of information-processing skills shows a much clearer upward trajectory across nearly all countries. The use of reading, writing, numeracy, ICT and problem-solving skills has seen widespread gains, although the magnitude differs. Writing and ICT skills use exhibit significant increases, with the latter standing out as one of the most dynamic areas of change. The increase in ICT use is particularly pronounced in Spain, Chile and Ireland, pointing to a strong intensification of digital tool use in the workplace (see Box 3.1 for more analysis on the evolution of the use of ICT skills in the last decade). The use of reading and numeracy skills also increased, albeit more moderately, with countries such as Lithuania, Italy, France and Ireland reporting above-average increases. The use of problem solving in the workplace presents a more nuanced picture. While some countries such as Ireland, New Zealand and Estonia record large increases, others including Italy and Poland display small declines. This suggests that although workplaces are becoming more digital and data-intensive, the extent to which they require employees to engage in complex, non-routine problem solving is uneven.

Figure 3.1. Change in the use of information-processing skills at work between PIAAC cycles



Source: 2023, 2018, 2015, 2012 Survey of Adult Skills.

Figure 3.2. Change in the use of generic skills at work between PIAAC cycles



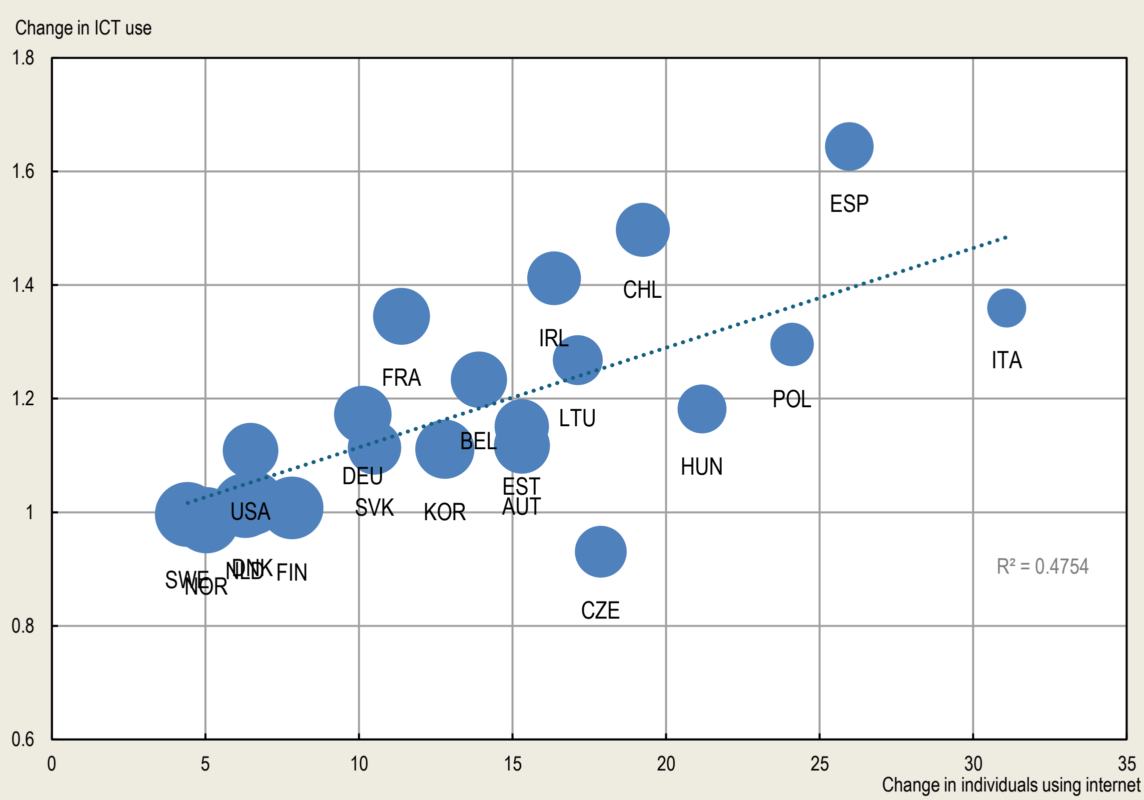
Source: 2023, 2018, 2015, 2012 Survey of Adult Skills.

Box 3.1. The evolution of the use of ICT skills in the last decade

Studying the correlation between changes in ICT skills use at work and internet use between 2012 and 2023 is particularly interesting because it captures a period of rapid digital transformation, marked by the diffusion of smartphones, the rise of platform economies, and the shift to remote work and online services accelerated by the COVID-19 pandemic. ICT skills are not only a prerequisite for meaningful internet use but also a determinant of how individuals benefit from digital technologies, whether in accessing information, improving employability, or engaging socially and politically. At the same time, greater internet use can reinforce skill acquisition through practice, exposure, and online learning opportunities. Analysing how these two dimensions evolved together over the past decade provides insights into digital inclusion, inequality, and the extent to which technological change has translated into broader participation in the digital economy.

Figure 3.3 illustrates a positive correlation between changes in the use of ICT skills at work between the two cycles of the Survey of Adult Skills and changes in the share of individuals using the internet over the same period. Countries that experienced larger increases in internet use, such as Spain, Italy, and Poland, also tended to record more pronounced growth in the use of ICT skills at work, reflecting the spreading of technology at work and in society. Conversely, countries like Sweden, Norway, Finland, and the United States, where internet use was already high in 2012, show only marginal increases in both internet use and the use of ICT skills at work, consistent with a saturation effect. These patterns highlight convergence, as late adopters catch up.

Figure 3.3. Change in ICT skills use at work and in individuals using internet over PIACC cycles



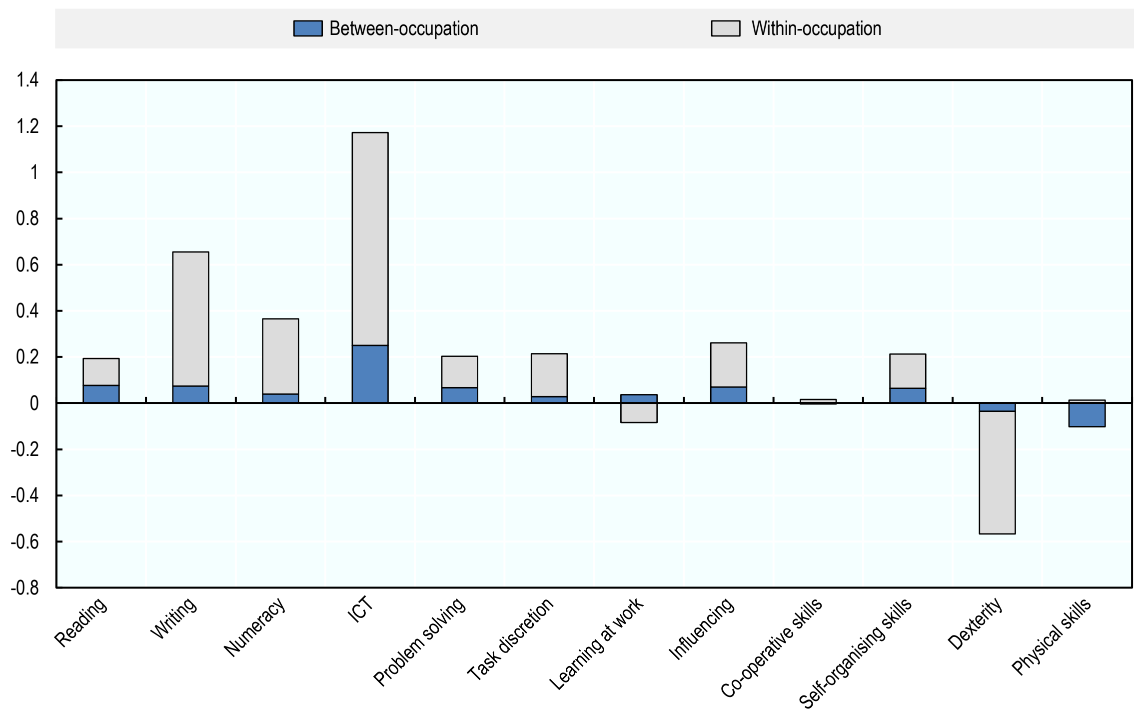
Note: The size of the bubble represents the share of individuals using the internet in 2012. For consistency, the country name is reported for Belgium and the United Kingdom, even if the Survey of Adult Skills is conducted only at subnational level – namely in the Flemish region and in England, respectively.
Source: 2023, 2018, 2025, 2012 Survey of Adult Skills; OECD.Stat – ICT Access and Usage by Individuals (2012 and 2023).

To better understand the drivers of the change in skills use at work over the past decade, a Blinder-Oaxaca decomposition is applied (Blinder, 1973[4]; Oaxaca, 1973[5]; Elder, Goddeeris and Haider, 2010[6]). This technique separates observed changes into two components. The "between-occupation" component captures the share of the change attributable to shifts in the composition of the workforce and job characteristics, such as education, occupation, industry, firm size, or contract type. The "within-occupation" component reflects differences in the way these same characteristics are associated with skills use between cycles. In this context, it measures how the relationship between individual and job attributes and the use of specific skills has evolved over time, once compositional changes are held constant. The technique is particularly useful for distinguishing between changes arising from who is employed in the economy and in which jobs and the changes linked to how work is organised and tasks are performed.

The results in Figure 3.4 indicate that the majority of the change in skills use between cycles of the Survey of Adult Skills is due to changes in skills use within occupations. This pattern suggests that changes within jobs – the way jobs are organised or the adoption of new technologies – have influenced changes in skills use more than structural changes in workforce composition. For instance, the large "within-occupation" increase in ICT use points to deeper technological integration within occupations that previously made limited use of digital tools. Similarly, the rise in writing, numeracy and problem-solving skills is only partially accounted for by observable factors such as higher education levels, implying that the content of jobs themselves has changed to require more of these competences. Similarly, the use of dexterity skills at work shows a pronounced decline over the past decade dominated by the unexplained component.

The limited contribution of the "between-occupation" component in most skill domains suggests that shifts in education, age, or occupational composition have played a secondary role in explaining the evolution of skills use. Instead, changes in technology, management practices, and work organisation have altered the underlying production of tasks. This evidence points to a labour market in which the way work is performed has evolved faster than the characteristics of the workforce itself, reinforcing the need for adult learning policies aimed at helping workers adapt to changes in the skill requirements of their own jobs more than to transition to new jobs.

Figure 3.4. Decomposition of the change in skills use

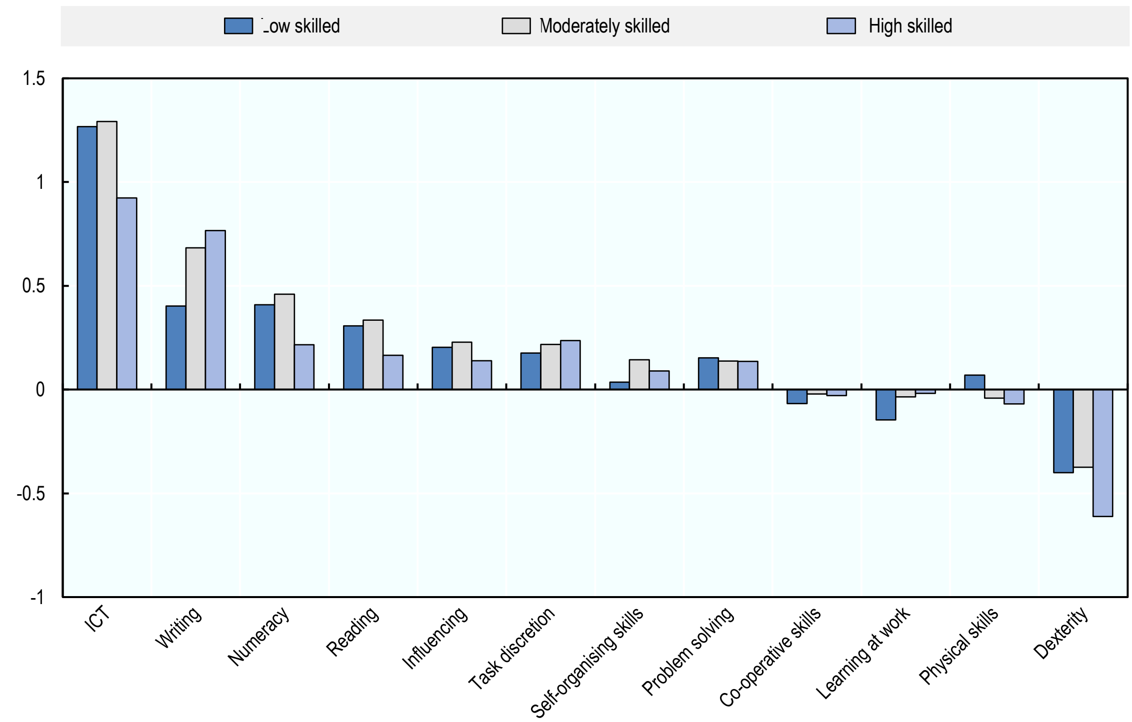


Note: The Figure presents results of a Blinder-Oaxaca decomposition of the change in skills use between PIAAC cycles. Each bar represents a separate regression. Controls include gender, age, age squared, educational attainment, literacy proficiency, occupation, industry, firm size, permanent contract, public employment, and country fixed effects. All coefficients are statistically significant (at the 1% significance level), except those of co-operative skills, which are not significant.
Source: 2023, 2018, 2025, 2012 Survey of Adult Skills.

How skills use is changing across occupations

Tracking how the use of skills at work evolves by occupation offers additional insights into shifting job requirements and the reorganisation of tasks within the labour market. Figure 3.5 shows that, for all occupation groups, the largest increases in skills use are observed in ICT, writing, and numeracy. While these trends highlight the pervasive integration of digital tools and communication tasks, the increase is particularly marked among workers in low- and medium-skilled occupations, suggesting that technological diffusion is no longer limited to high-skilled roles but has become a defining feature of work more broadly. Reading, influencing, and task discretion have also grown in all occupations, though to a lesser extent. By contrast, the use of physical skills and especially dexterity has declined substantially, most notably among high-skilled occupations, pointing to a continued shift away from manual requirements towards knowledge-intensive and cognitively demanding tasks.

Figure 3.5. Change in skills use at work between PIAAC cycles by occupation level

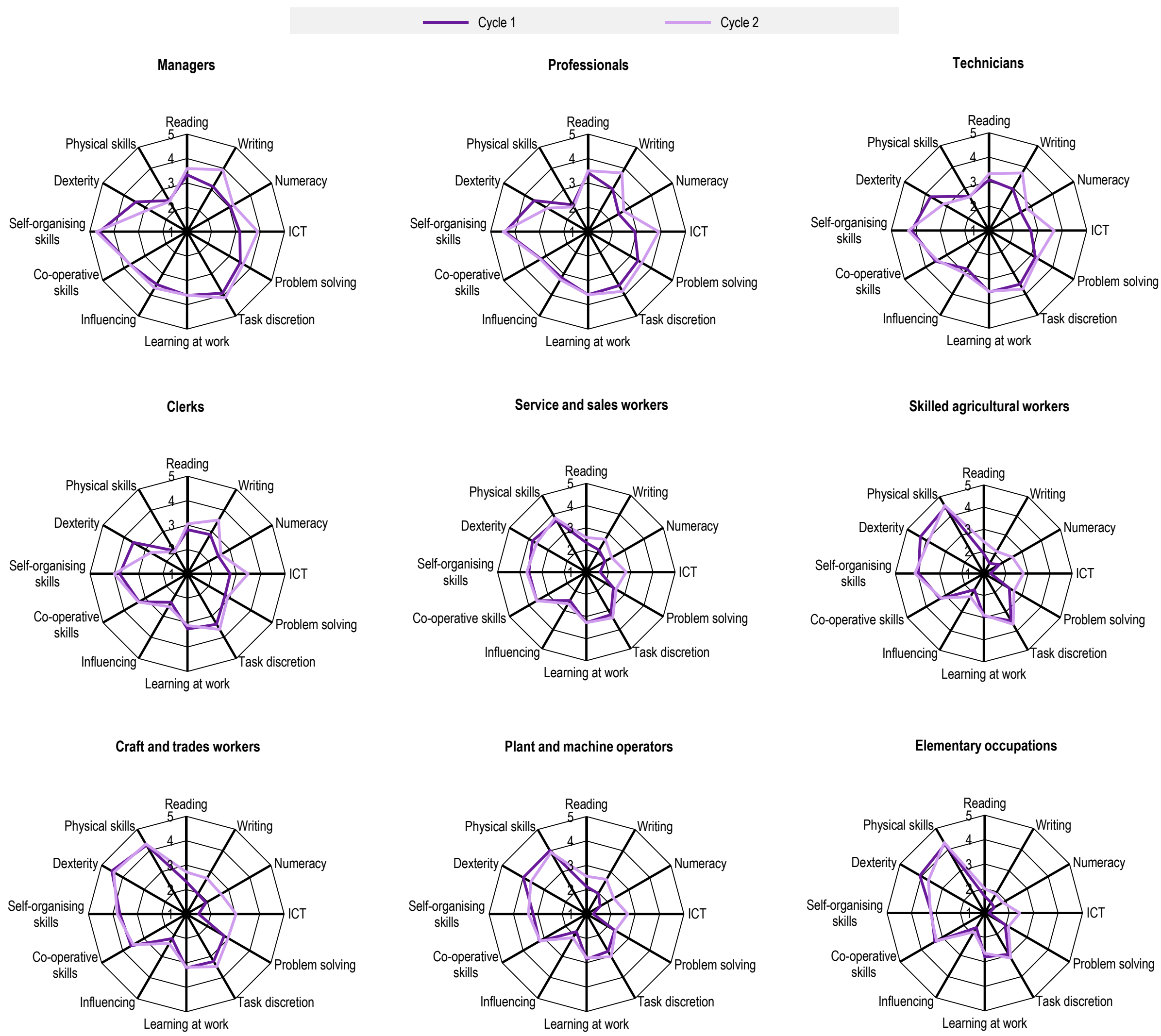


Note: Skill level is derived from ISCO 1-digit occupation codes: high skilled (1-3), moderately skilled (4-8), low skilled (9). Armed forces (0) are excluded. Skills are sorted by largest change for moderate-skilled occupations.
Source: 2023, 2018, 2015, 2012 Survey of Adult Skills.

Further examination of changes by occupation reveals additional heterogeneity (Figure 3.6). For example, although ICT use increased among all workers between 2012 and 2023, the increase has not been uniform. Skilled agricultural workers, such as livestock producers and forestry workers, recorded an increase twice as large as that of managers (1.5 compared with 0.7 points on the five-point scale used to measure skills use). Differences also emerge within the same skill group. Among medium-skilled occupations, clerks, including receptionists and bank tellers, experienced only a negligible increase in numeracy use (0.1 points), whereas craft and trades workers, such as plumbers and carpenters, saw a much larger rise of 0.7 points. Even for skills whose use has declined, the extent of the reduction differs between occupations. Craft and trades workers experienced almost no decline in the use of dexterity skills, while clerks registered a fall by 0.8 points.

These findings underline the uneven pace of change in skills demand among occupations. They point to the need for targeted training and upskilling policies that account for such variation. For workers in lower- and medium-skilled occupations, the strong rise in ICT and numeracy requirements highlights the importance of widening access to digital and foundational skills training. At the same time, the sharp reduction in dexterity-based work suggests that policies should anticipate structural shifts in manual occupations and prepare workers for increasingly knowledge-oriented tasks in their own jobs.

Figure 3.6. Average skills use by occupation and PIAAC cycle



Source: 2024, 2018, 2015, 2023 Survey of Adult Skills.

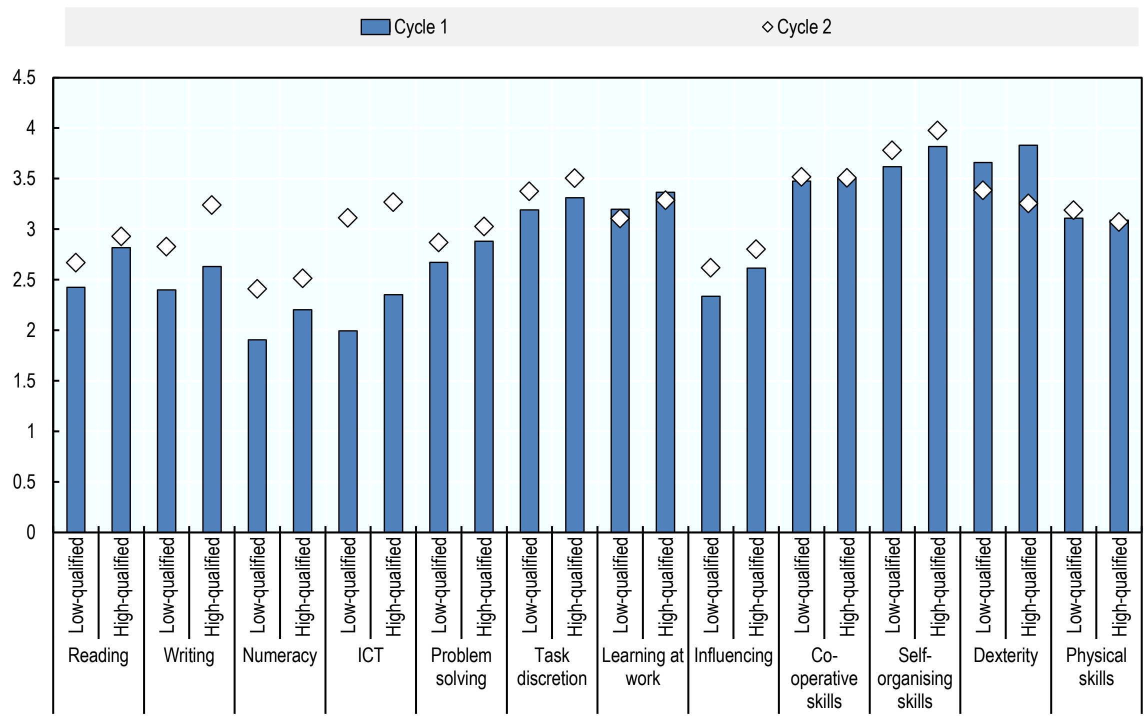
Are low-qualified workers catching up in terms of skills use?

Figure 3.7 summarises the evolution of skills use at work for low- and high-qualified adults between the first and second cycles of the Survey of Adult Skills. The estimates derive from OLS regressions controlling for gender, age, immigration background, literacy proficiency, occupation, industry, firm size, employment status, contract type, public-sector employment and country fixed effects. In nearly all skill domains, the results point to an increase in the frequency with which adults report using their skills at work that is stronger among low-qualified workers. In Cycle 1, these workers reported substantially lower frequency of skills use compared with high-qualified adults, but the gap has narrowed in almost all areas by Cycle 2. The increase is particularly pronounced for the use of numeracy, ICT, and influencing skills, which are core to work in more complex work environments.

These patterns indicate a process of convergence in skills use between qualification groups and are consistent with earlier evidence in this chapter showing that workers in low- and medium-skilled occupations are increasingly engaging in tasks requiring higher levels of ICT, numeracy, reading, influencing and problem-solving skills. The results therefore confirm that the process of job upgrading is not confined to high-skilled occupations but extends across the qualification spectrum, reflecting an overall shift in the nature of work towards greater use of a wide range of skills.

Figure 3.7. Evolution of skills use at work for low- and high-qualified adults

Predicted skills use at work by PIAAC cycle



Note: The Figure represents the marginal effects of OLS regressions controlling for gender, age, age squared, immigration background, literacy proficiency, occupation, industry, firm size, full-time work, permanent contract, public employment, and country fixed effects. Low-qualified workers are defined as those with up to lower secondary education, while the rest are defined as high-qualified workers. All coefficients are statistically significant (at the 1% significance level).
Source: 2023, 2018, 2015, 2012 Survey of Adult Skills.

To understand the mechanisms driving the fact that low-qualified workers have experienced a stronger rise in the use of skills at work than their high-qualified counterparts, it is important to distinguish between two possible explanations. The first relates to compositional shifts: low-qualified workers may now be employed in different types of occupations that are inherently more skill-intensive. The second involves within-occupation adjustments, in which the content of existing jobs has evolved and become more demanding in terms of skill requirements. Formally, changes in the average skills use of low-qualified workers can be decomposed into these two components:

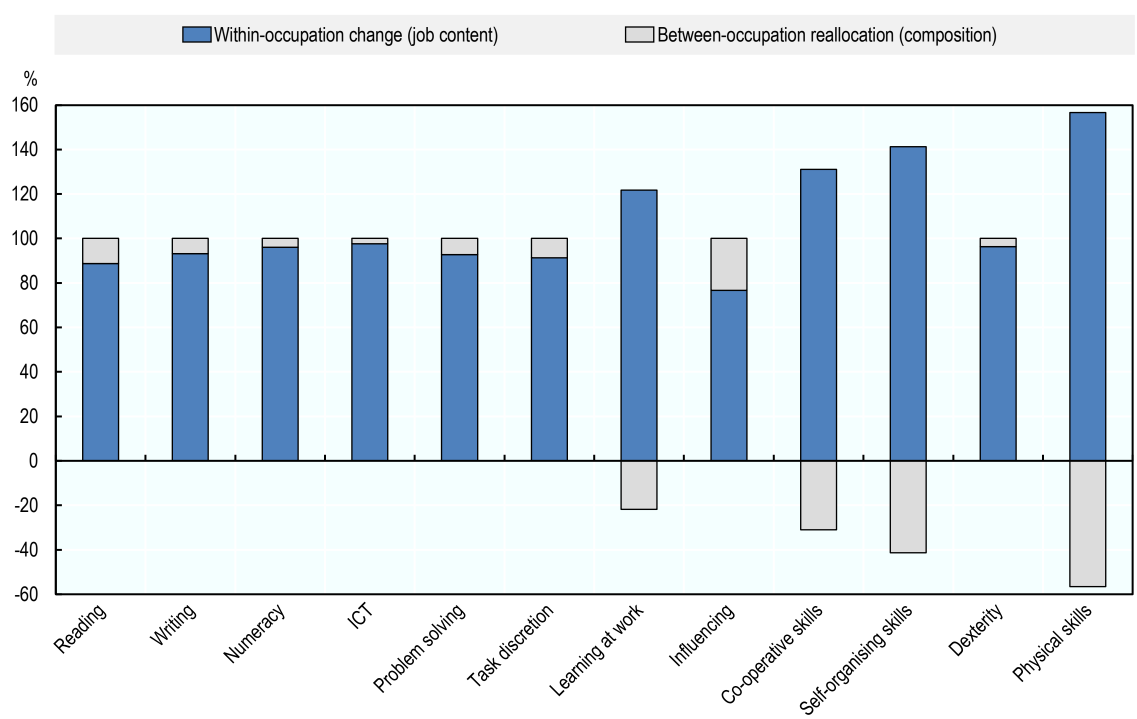
$$\Delta\bar{s} = \sum_j (\bar{s}_{j,2} - \bar{s}_{j,1}) w_{j,1} + \sum_j \bar{s}_{j,1} (w_{j,2} - w_{j,1})$$

Equation 3.1.

where $\bar{s}_{j,c}$ is the average skills use in occupation *j* in cycle *c*, $w_{j,c}$ is the employment share of low-qualified workers in occupation *j* in cycle *c*. The first term in the decomposition captures within-occupation changes, reflecting the evolution of skill requirements within occupations over time, whereas the second term captures between-occupation reallocation, indicating whether workers have moved into occupations that use skills more intensively.[2] This analytical framework follows well-established approaches in the labour economics literature, including the shift-share decomposition methods proposed by Freeman, Ganguli and Handel (2020[7]) and by Caunedo, Keller and Shin (2023[8]), which have been used to examine changes in task content and job structure over time. Both studies highlight that much of the evolution in the nature of work stems from transformations within occupations rather than large-scale shifts between them.

Figure 3.8 summarises the results of this decomposition for low-qualified workers. For each domain of skills use, the total change in predicted skills utilisation between cycles of the Survey of Adult Skills is separated into within-occupation and between-occupation components. The figure shows that – in line with the recent economic research cited above – the bulk of the increase in skills use among low-qualified workers arises from within-occupation changes. In other words, most of the observed catching-up effect is explained by jobs themselves becoming more skill-intensive, rather than by low-qualified workers moving into new, more demanding occupations. The within-occupation component is positive and substantial in almost all skill domains, particularly for the use of ICT skills, learning at work, co-operative skills, and self-organisation, which are critical to adapt to technological and organisational changes in the workplace (Box 3.2 provides additional insights on which specific ICT skills have increased in use at work for the low qualified). By contrast, the contribution of between-occupation reallocation is relatively modest and, for some skills, even negative.

Figure 3.8. Decomposition of skills use change for the low qualified



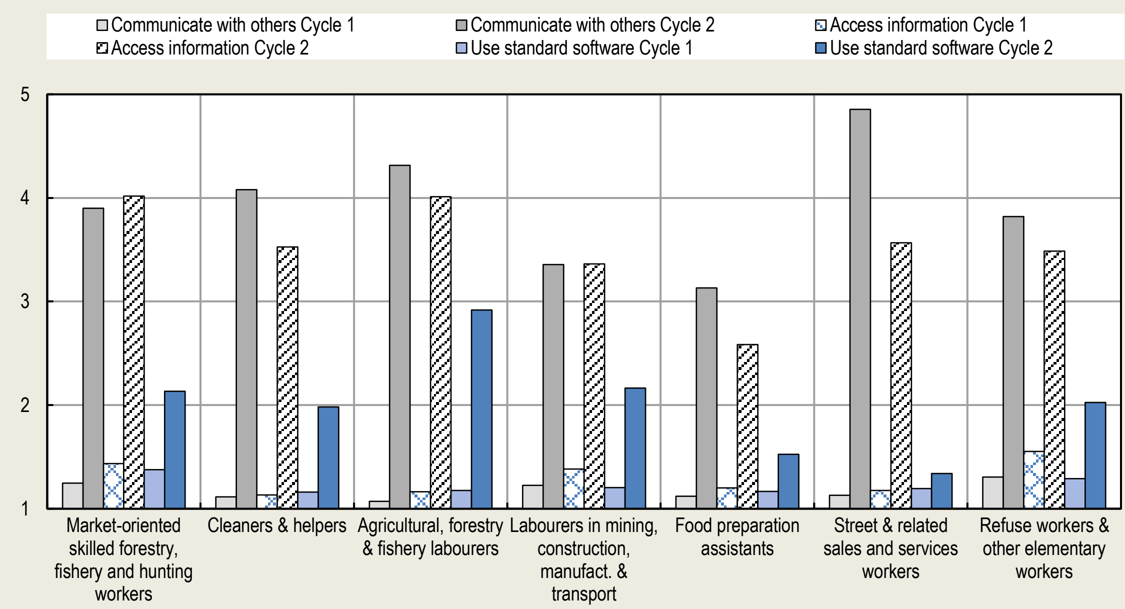
Note: The Figure restricts the analysis to low-qualified workers, defined as those with up to lower secondary education.
Source: 2023, 2018, 2015, 2012 Survey of Adult Skills.

Box 3.2. The more frequent use of ICT skills for low-qualified workers

The case of the use of ICT skills is particularly interesting, as, taken together, the evidence presented in Figure 3.7 and Figure 3.8 indicates that: 1) the skills displaying the greatest increase in workplace use between cycles of the Survey of Adult Skills for low-qualified workers are those related to ICT, and 2) almost all of this growth stems from the fact that existing jobs held by low-qualified workers have become more demanding in terms of the use of ICT skills.

To illustrate this point more precisely, the composite index of ICT skills use can be disaggregated to examine the evolution of its underlying components over the past decade for a subset of detailed occupations. Figure 3.9 presents data on the frequency of use of selected ICT skills in (2-digit ISCO) occupations where, in 2012, more than one-third of workers were low-qualified. While in Cycle 1 of PIAAC workers in these occupations reported never using digital tools for communication, by 2023 nearly all of them used applications such as email or internet-based calls at least once per week. The increase is especially marked among street and related sales and service workers, whose use of digital communication tools shifted from "Never" to almost "Every day". A similar pattern emerges for the use of the internet to access information, which has become substantially more frequent across all low-qualified occupational groups. Remarkably, even the use of standard software, such as spreadsheets and word processors, has risen considerably. For example, agricultural, forestry, and fishery labourers – who in 2012 reported almost no engagement with such tools – now use electronic documents, spreadsheets, or presentation software at least once per month.

Figure 3.9. Evolution of the use of ICT skills at work for selected occupations



Note: Caution is required to interpret these trends, as variables are differently phrased in the Cycle 1 and Cycle 2 PIAAC questionnaires – see the Annex for the exact variables used in each cycle.
Source: 2023, 2018, 2015, 2012 Survey of Adult Skills.

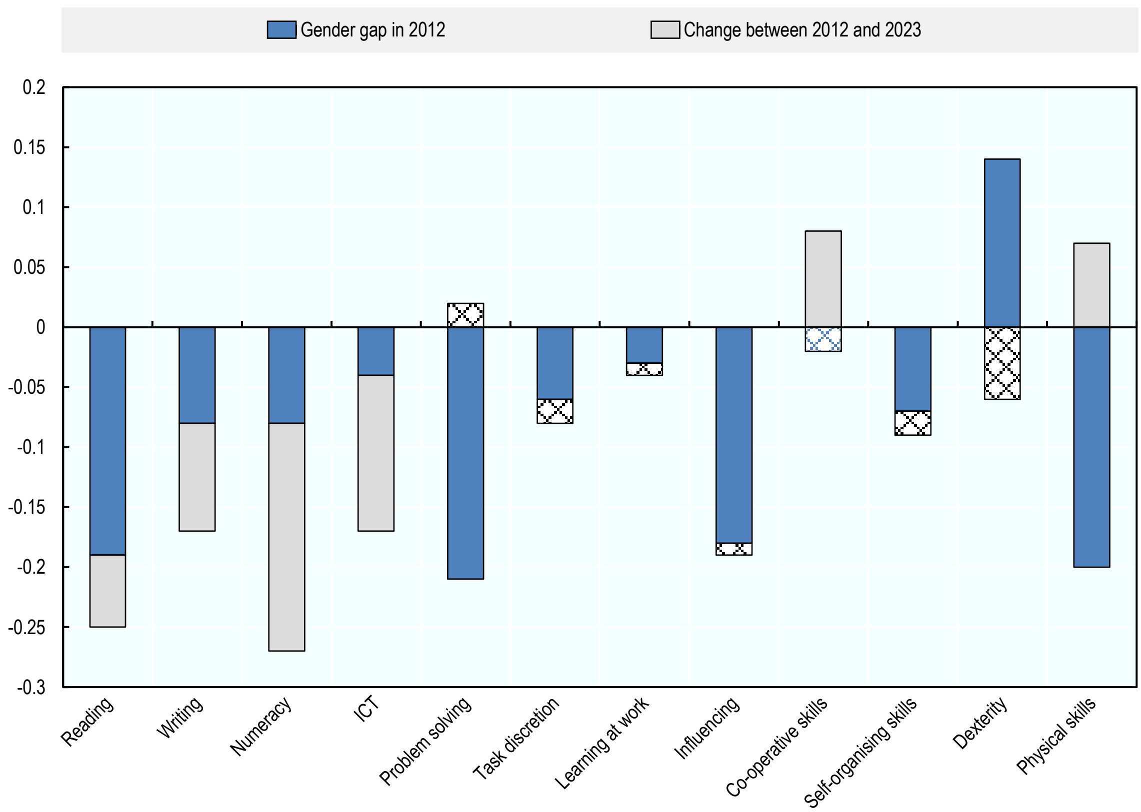
Are women bridging the gender gap in skills use?

Chapter 1 of this report found substantial disparities between men and women in the frequency of skills use at work (see, for instance, Figure 1.7). It is therefore interesting to assess whether there is evidence of a catching-up between the two cycles of the Survey of Adult Skills. Figure 3.10 summarises OLS coefficients from regressions of skills use on a gender dummy interacted with a dummy indicating the reference cycle. The blue bars show the baseline gender gap in the earlier cycle and the grey bars report the change between cycles. Two results stand out. First, for most information-processing skills including reading, numeracy, writing, and ICT the change coefficients are negative and statistically significant. The use of numeracy and ICT skills exhibits the largest deterioration in relative terms with the change coefficient implying a widening of the gap rather than convergence. The use of reading and writing also display further negative movement. By contrast, most of the other skills use present no statistically significant trend across cycles. This indicates not only no systematic catching up of women, but actually a substantial deterioration of the gender gap in skills use at work over time. Only two domains present a significant positive change over time. Notably, use of co-operative skills shows a positive and relatively large change coefficient indicating that the within-occupation gender gap in reported use of co-operative skills has declined between cycles. Physical skills also register a positive change coefficient, although the baseline disadvantage for women is large and not fully offset by the change.

These findings suggest that reducing the gender gap in skills use remains a priority requiring workplace-level interventions that address how tasks are allocated and that increase the degree of autonomy and discretion available to women. Complementary measures should strengthen the use of numeracy and ICT skills in everyday job contexts, as well as promote management practices that systematically review within-firm task assignment.

Figure 3.10. Gender gaps in skills use at work over PIAAC cycles

OLS coefficients



Note: The Figure represents the coefficient of OLS regressions of skills use on gender interacted with a PIAAC cycle dummy. Coefficients are adjusted for age, age squared, immigration background, educational attainment, literacy proficiency, occupation, industry, firm size, full-time work, permanent contract, public employment, and country fixed effects. Each bar represents a separate regression. Shaded bars represent statistically not significant results, while all the other coefficients are statistically significant (at least at the 10% significance level).
Source: 2023, 2018, 2015, 2012 Survey of Adult Skills.

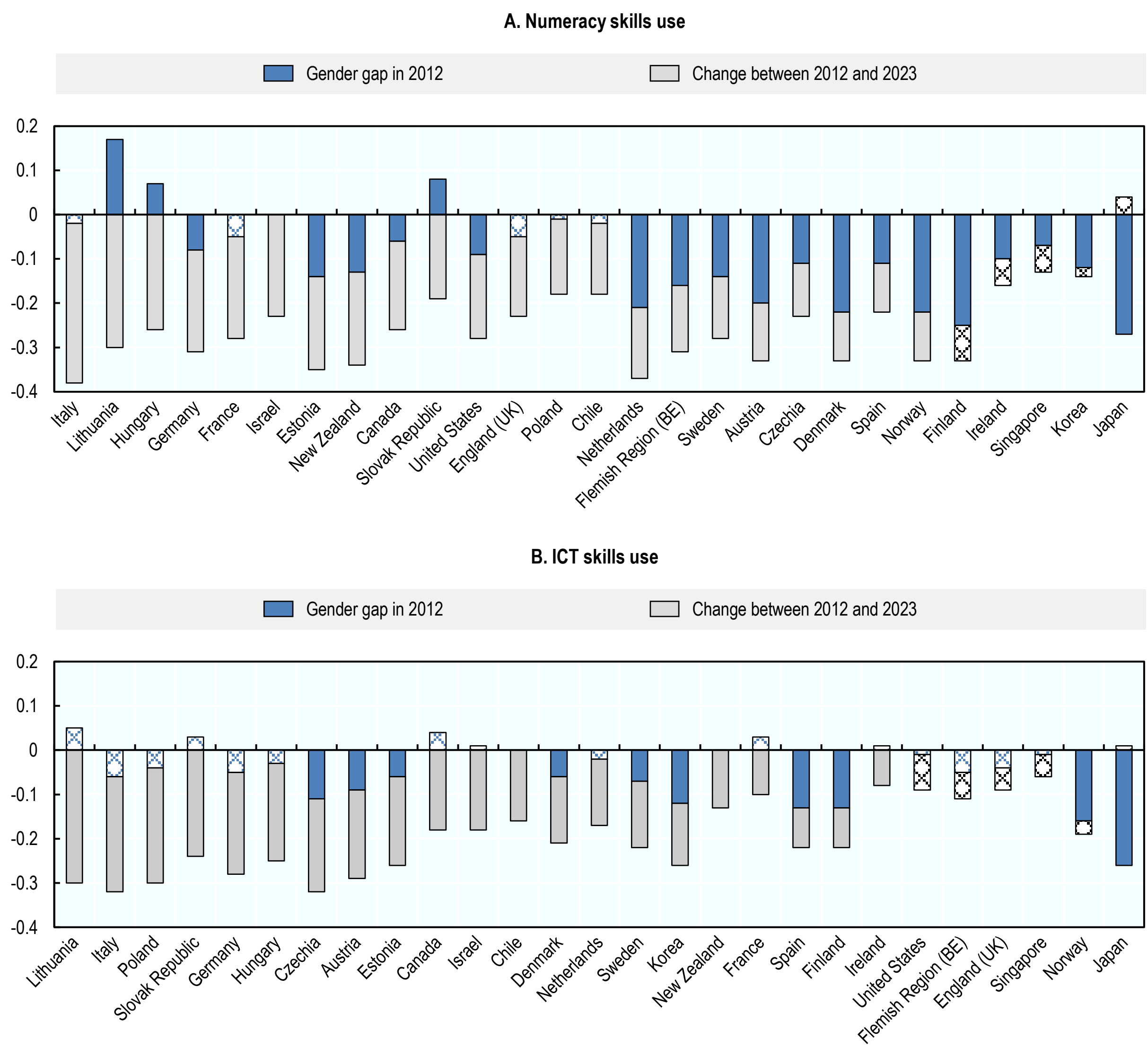
Cross-country comparisons provide a better understanding of how the gender gap in skills use evolves over time. Figure 3.11 focusses on two domains where the gender gap in skills use was found to be most pronounced and widening between cycles of the Survey of Adult Skills, namely numeracy and ICT skills. Overall, the chart shows that the size of the gap differs considerably between countries, suggesting that national labour market structures, occupational segregation patterns and policy contexts may play a significant role.

Panel A shows that the gender gap in the use of numeracy skills remains sizeable in many countries. In the first cycle of the Survey of Adult Skills, women used numeracy-related skills less frequently than men in almost all countries, with particularly large negative coefficients in Japan and in some of the Nordic countries, like Finland, Norway and Denmark. Over the following decade, the situation generally worsened. The grey bars that represent changes between the two cycles are negative in a majority of cases, suggesting that women's relative use of numeracy skills declined further. However, there are exceptions. In Japan and Finland, where the initial gap was among the largest, the coefficients for change are close to zero, indicating that the gap did not worsen. This relative stability contrasts with the general pattern of widening gaps observed elsewhere.

In the use of ICT skills (Panel B), many countries displayed only a modest or statistically insignificant gender gap in 2012. The pattern over time suggests that the gap has emerged or widened in the most recent cycle. The change coefficients are negative for most countries, indicating that men have increased their use of ICT skills at work relative to women. The emergence of this new gender gap may reflect structural changes in digitalisation and occupational upgrading, where male-dominated roles (even with broader sectors and occupations) have been more successful in integrating ICT-intensive work tasks. Nonetheless, a few countries stand out for showing little deterioration or some improvement, notably Japan and Norway, which had large gender differences in ICT use in 2012 but have not experienced further divergence.

Figure 3.11. Trends in gender gaps in the use of selected skills at work by country

OLS coefficients



Note: The Figure represents the coefficient of OLS regressions of skills use on gender interacted with a PIAAC cycle dummy. Coefficients are adjusted for age, age squared, immigration background, educational attainment, literacy proficiency, occupation, industry, firm size, full-time work, permanent contract, public employment, and country fixed effects. Each bar represents a separate regression. Shaded bars represent statistically not significant results, while all the other coefficients are statistically significant (at least at the 10% significance level). Countries are sorted in descending order according to the magnitude of the change in skills use between 2012 and 2023.
Source: 2023, 2018, 2015, 2023 Survey of Adult Skills.

Figure 3.12 provides further insight into the mechanisms underpinning the widening gender gap in numeracy skills use by examining how patterns differ between qualification levels, occupations, and industries. The predicted values shown are obtained from OLS regressions controlling for individual and job characteristics, isolating how numeracy skills use evolves over time by gender within comparable groups. In all panels, men exhibit steeper increases in numeracy use between 2012 and 2023, controlling for a set of individual and job characteristics, confirming that men have benefited more from changes in work organisation and technological content of tasks.

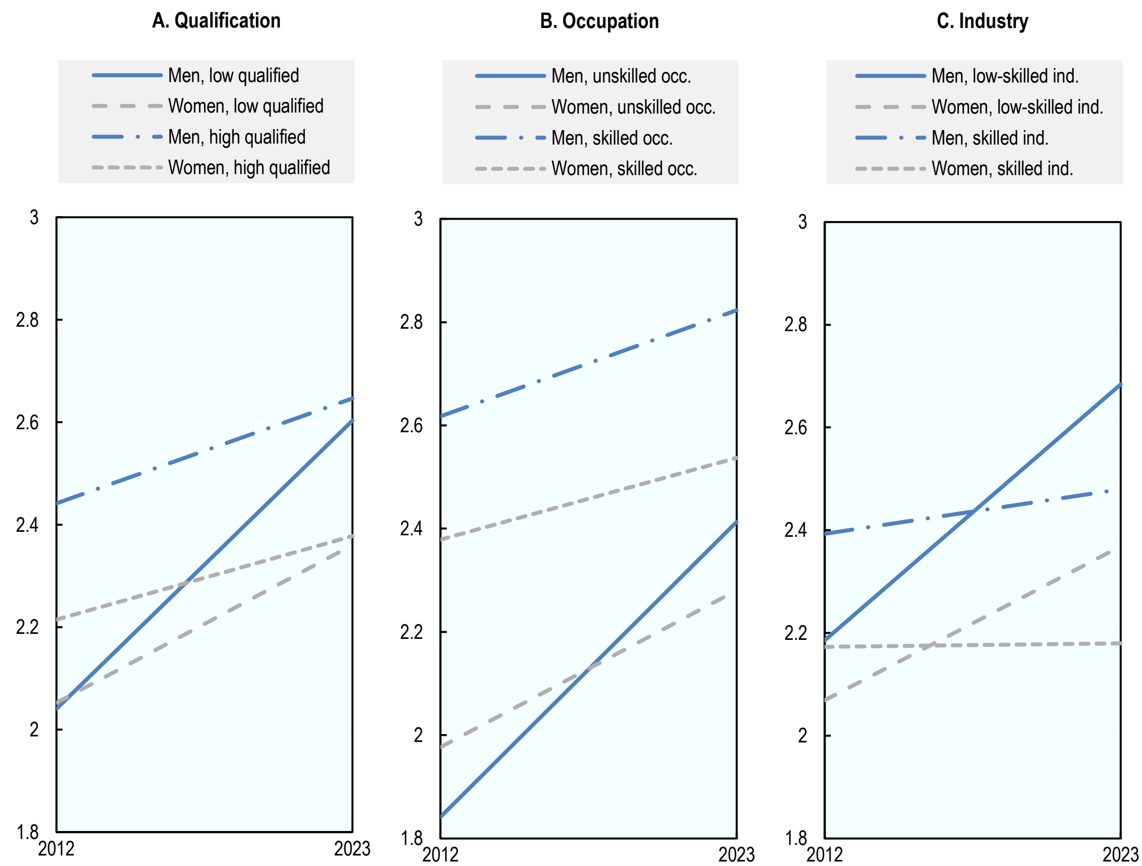
Panel A focusses on qualification levels and reveals a substantial divergence. In 2012, low-qualified men and women used numeracy skills at a similar level. Over the following decade, however, the trajectory of low-qualified men shows a pronounced upward slope, almost converging with that of high-qualified men by 2023. Low-qualified women have also increased their numeracy use, reaching the level of high-qualified women, but the latter group remains substantially below men with similar educational attainment. This pattern suggests that even when educational disparities narrow, gendered patterns of task allocation and occupational segregation continue to limit the extent to which women apply numeracy skills at work. These results are consistent with previous research indicating that women's underuse of numeracy skills even when controlling for proficiency levels and educational attainment (OECD, 2019[9]).

Panel B compares trends by occupational skill level. Here, the evolution among workers in unskilled occupations is particularly striking. While men in unskilled occupations started from lower levels of numeracy use in the first cycle, their numeracy use has increased much more than that of women in similar occupations. By 2023, men in unskilled occupations report using numeracy skills almost as frequently as skilled women, underscoring the gendered dimension of task allocation even within low-skill occupations. The gap among skilled workers remains large and has not narrowed over time. These results reinforce the idea that the workplace environment and job content – not only education – play a decisive role in explaining gender disparities in skills utilisation.

Panel C, which disaggregates by industry, provides one of the most revealing findings. The analysis distinguishes skilled industries – those with more than 60% of tertiary-educated workers, such as ICT, finance and education – from low-skilled ones. In 2012, men in low-skilled industries used numeracy skills at levels similar to those of women in skilled industries. Over the subsequent decade, however, male workers in low-skilled industries experienced a sharp increase in numeracy use, while women in skilled industries saw no gain. This divergence highlights that even in sectors characterised by high levels of education, women's opportunities to apply numeracy skills have not expanded. The evidence points to persistent gender segregation within industries, where female workers are concentrated in roles with less analytical content and limited exposure to numeracy-intensive tasks.

Overall, these findings suggest that addressing gender disparities in skills use requires policy interventions that go beyond improving women's skills and focus instead on workplace practices, job design, and career progression pathways that enable women to apply these skills throughout their working lives.

Figure 3.12. Evolution of the predicted use of numeracy skills at work by gender



Note: The Figure represents the marginal effects of OLS regressions controlling for age, age squared, immigration background, literacy proficiency, educational attainment (not in Panel A), occupation (not in Panel B), industry (not in Panel C), firm size, full-time work, permanent contract, public employment, and country fixed effects. High-qualified workers in Panel A are defined as those with a post-secondary or tertiary education. Skilled occupations in Panel B are based on ISCO 1-digit codes, and, as standard in the literature, include "Managers", "Professionals", and "Technicians". Skilled industries in Panel C have been selected as those industries at ISIC 1-digit level that have a share of tertiary-educated workers in PIAAC higher than 60%; namely, "Info & communication", "Financial & insurance", "Professional, scientific & technical", "Education", and "Extraterritorial". All coefficients are statistically significant (at the 1% significance level).
Source: 2023, 2018, 2015, 2012 Survey of Adult Skills.

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Notes

[1] Despite efforts to make the composite indices of skills use comparable over time, caution is still needed when interpreting these trends, as some variables may be phrased differently in the Cycle 1 and Cycle 2 PIAAC questionnaires.

[2] Note that this technique – typically called "shift-share decomposition" – is conceptually similar to the Blinder-Oaxaca decomposition used to construct Figure 3.4, in that it separates total change into composition and within-category effects. However, it is not the same method in the strict econometric sense, because it does not involve regression coefficients, but it uses observed averages to explain changes over time within a single group (in this case, low-qualified workers).

Annex A. Indicators of skills use at work in PIAAC

Table A A.1. Overlap of skills use indicators across PIAAC cycles

Indicator	PIAAC Cycle 1 variables	PIAAC Cycle 2 variables	Overlap across Cycles
Information-processing skills			
Reading	G_Q01a: In your current job, how often do you usually read directions or instructions? G_Q01b: In your current job, how often do you usually read letters, memos or e-mails? G_Q01c: In your current job, how often do you usually read articles in newspapers, magazines or newsletters? G_Q01d: In your current job, how often do you usually read articles in professional journals or scholarly publications? G_Q01e: In your current job, how often do you usually read books? G_Q01f: In your current job, how often do you usually read manuals or reference materials? G_Q01h: In your current job, how often do you usually read diagrams, maps or schematics?	F2_Q01a: In your current job, how often do you usually read directions or instructions? F2_Q01b: In your current job, how often do you usually read letters, memos or e-mails? F2_Q01c: In your current job, how often do you usually read articles in newspapers, magazines or newsletters? F2_Q01d: In your current job, how often do you usually read books, scholarly publications, or articles in professional journals? F2_Q01e: In your current job, how often do you usually read manuals or reference materials? F2_Q03b: In your current job, how often do you usually use maps, plans or GPS for finding directions and locations?	High
Writing	G_Q02a: In your current job, how often do you usually write letters, memos or emails? G2_Q02b: In your current job, how often do you usually write articles for newspapers, magazines or newsletters? G2_Q02c: In your current job, how often do you usually write reports? G2_Q02d: In your current job, how often do you usually fill in forms?	F2_Q02a: In your current job, how often do you usually write letters, memos or emails? F2_Q02b: In your current job, how often do you usually write reports or articles? F2_Q02c: In your current job, how often do you usually fill in forms?	High
Numeracy	G_Q03b: In your current job, how often do you usually calculate prices, costs or budgets? G_Q03c: In your current job, how often do you usually use or calculate fractions, decimals or percentages? G_Q03f: In your current job, how often do you usually prepare charts, graphs or tables? G_Q03g: In your current job, how often do you usually use simple algebra or formulas? G_Q03h: In your current job, how often do you usually use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques? G_Q01g: In your current job, how often do you usually read bills, invoices, bank statements or other financial statements?	F2_Q03a: In your current job, how often do you usually undertake calculations, such as calculating prices, costs or quantities? F2_Q03c: In your current job, how often do you usually undertake measurements such as lengths, weights, temperature, dosages, areas or volumes? F2_Q03d: In your current job, how often do you usually read and prepare charts, graphs or tables? F2_Q03e: In your current job, how often do you usually use advanced mathematics or statistics? F2_Q01f: In your current job, how often do you usually read bills, invoices, bank statements or other financial statements?	Moderate
ICT skills	G_Q05a: In your current job, how often do you usually use email? G_Q05c: In your current job, how often do you usually use the internet in order to better understand issues related to your work?	F2_Q05a: In your current job, how often do you usually communicate with others (e.g. via emails, social networking sites, or internet calls)? F2_Q05c: In your current job, how often do you usually access information (e.g. use a search engine, find	Moderate

Indicator	PIAAC Cycle 1 variables	PIAAC Cycle 2 variables	Overlap across Cycles
	G_Q05d: In your current job, how often do you usually conduct transactions on the internet, for example buying or selling products or services, or banking? G_Q05e: In your current job, how often do you usually use spreadsheet software, for example Excel? G_Q05f: In your current job, how often do you usually use a word processor, for example Word? G_Q05g: In your current job, how often do you usually use a programming language to programme or write computer code? G_Q05h: In your current job, how often do you usually participate in real-time discussions on the internet, for example online conferences, or chat groups?	information, or read documents)? F2_Q05d: In your current job, how often do you usually create or edit electronic documents, spreadsheets or presentations? F2_Q05e: In your current job, how often do you usually use specialised software (e.g. for computer-aided design, for processing or analysis of data, sound and images, or quality control)? F2_Q05f: In your current job, how often do you usually use a programming language to programme software or websites?	
Problem solving	F_Q05b: How often are you usually confronted with complex problems that take at least 30 minutes to find a good solution?	H2_Q06b: How often are you usually confronted with complex problems that take at least 30 minutes to find a good solution?	Identical
	Generic skills		
Task discretion	D_Q11a: To what extent can you choose or change the sequence of your tasks? D_Q11b: To what extent can you choose or change how you do your work? D_Q11c: To what extent can you choose or change the speed or rate at which you work?	H2_Q08a: To what extent can you choose or change the sequence of your tasks? H2_Q08b: To what extent can you choose or change how you do your work? H2_Q08c: To what extent can you choose or change the speed or rate at which you work?	Identical
Learning at work	D_Q13a: In your own job, how often do you learn new work-related things from co-workers or supervisors? D_Q13b: How often does your job involve learning-by-doing from the tasks you perform? D_Q13c: How often does your job involve keeping up to date with new products or services?	H2_Q09a: To what extent can you choose or change how often does your current job involve learning new things? H2_Q09b: To what extent can you choose or change how often does your current job involve learning-by-doing from the tasks you perform? H2_Q09c: To what extent can you choose or change how often does your current job involve keeping up to date with new products or services?	Moderate
Influencing skills	F_Q02b: How often does your current job usually involve instructing, training or teaching people? F_Q02c: How often does your current job usually involve making speeches or giving presentations in front of five or more people? F_Q04a: How often does your current job usually involve persuading or influencing people? F_Q04b: How often does your current job usually involve negotiating with people either inside or outside your firm or organisation?	H2_Q03b: How often does your current job usually involve instructing, training or teaching people? H2_Q03c: How often does your current job usually involve making speeches or giving presentations in front of five or more people? H2_Q05a: How often does your current job usually involve persuading or influencing people? H2_Q05b: How often does your current job usually involve negotiating with people either inside or outside your firm or organisation?	Identical
Co-operative skills	F_Q01b: In your current job what proportion of your time do you usually spend co-operating or collaborating with co-workers?	H2_Q01: In your current job what proportion of your time do you usually spend co-operating or collaborating with co-workers?	Identical
Self-organising skills	F_Q03a: How often does your current job usually involve planning your own activities? F_Q03c: How often does your current job usually involve organising your own time?	H2_Q04a: How often does your current job usually involve planning your own activities? H2_Q04b: How often does your current job usually involve organising your own time?	Identical
Dexterity	F_Q06c: How often does your current job usually involve using skill or accuracy with your hands or fingers?	H2_Q07b: How often does your current job usually involve using hands or fingers for precision work?	High
Physical skills	F_Q06b: How often does your current job usually involve working physically for a long period?	H2_Q07a: How often does your current job usually involve working physically for a long period?	Identical

Getting Skills Right

How Workers Use, or Don't Use, their Skills in the Workplace

Drawing on the latest OECD Survey of Adult Skills (PIAAC), this report provides new evidence of a broken link between skills proficiency and skills use, revealing that many highly skilled workers have limited opportunities to deploy their talents. By linking skills use to wages, productivity, inequality and job satisfaction, the report demonstrates why effective skills use matters for both economic performance and worker well-being. It also takes a unique look at how skills use has evolved over the past decade, identifying where and for whom talent remains underutilised across countries, occupations and demographic groups. This analysis provides valuable insights into the broader social and economic impact of skills mismatches, offering a timely call for policy changes to bridge the gap between skills proficiency and skills use.

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