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Skills Ready: Education, Opportunity and AI

Exploring the socio-economic considerations of AI in education

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United Nations
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Education 2030

Published in 2026 by the United Nations Educational, Scientific and Cultural Organization,
7, place de Fontenoy, 75352 Paris 07 SP, France

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Designed by Noam Le Pottier

Printed by UNESCO

Printed in France

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Acknowledgment

This publication was produced with the guidance of Borhene Chakroun, Director of the Policies and Lifelong Learning Systems Division of the United Nations Educational, Scientific and Cultural Organization (UNESCO).

The text was written by Divya Sharma and Claudia Pompa, with support from Chloe Corbino.

The authors would like to express their sincere appreciation to Roisin Murphy, Head of Global Sustainability at KPMG International, and to the KPMG team, for their contribution and support throughout the development of this research.

The following reviewers also provided valuable feedback as members of the Advisory Expert Group: Samantha Gloede - Global Head of Risk Services and Trusted AI Leader, KPMG International; Patricia Justino - Director, UNU Wider; Mina Patel - Head of Research Future of English programme, British Council and Friedrich Huebler - Head of UNEVOC, UNESCO.

Noam Le Pottier was responsible for the graphic design and layout. Laurence Blair edited the report. Erin Chemery and Patrick Devaney provided project management support. Yael Thomas and Nastassja Marie Matrundola provided administrative support.

Executive summary

Digital technologies, especially artificial intelligence (AI), are rapidly reshaping the global economy, creating new jobs and redefining existing ones. This is prompting education systems to undergo a digital transformation: integrating digital and AI skills into curricula, training and assessments. But not all have access to new technologies and the ability to benefit from upskilling or reskilling. For example, middle-income economies account for more than half of global traffic on Generative AI (GenAI) platforms, far outstripping their share of GDP, while low-income economies account for less than 1% (Liu and Wang, 2024). Without broad access to relevant skills and infrastructure, the benefits of AI adoption may be unevenly distributed: potentially widening divides in education, employment and economic opportunity between countries, communities and individuals.



Digital transformation in education goes beyond adding devices or Digitizing records: it means redesigning how education systems operate, from teaching and assessment to management and decision-making, by integrating digital technology and data (Reinitz, 2020; Rajasekaran et al., 2024).



Digital skills are the abilities to use digital devices, communication applications and networks to find and manage information, create and share content, communicate and collaborate, and solve problems in life, learning and work (UNESCO, 2018; 2023a). They range from basic skills such as using a device, email and web search, through intermediate skills in software and data management, to advanced skills such as data analysis and programming (ITU Database).



AI skills build on digital skills and span a continuum: the ability to use AI tools and judge their outputs critically (AI literacy); the ability to apply AI effectively within a field of expertise (applied AI skills); and the specialist technical skills needed to build and maintain AI systems (specialist AI skills) (UNESCO, 2024c; OECD and European Union, 2026; OECD, 2026f).

Total global spending on education (by governments, households and donors combined) reached US$5.8 trillion in 2022 (The World Bank and UNESCO, 2024). But how much of that was invested in digital transformation and building the skills learners need is unclear. The resources available for learning are also tightening. Total education spending grew by only 1.8% a year between 2010 and 2022 after inflation, more slowly than the world economy (The World Bank and UNESCO, 2024). Funding for education in low- and middle-income countries from donors and international organizations is projected to fall by up to 30% between 2023 and 2027 (UNESCO, 2026d).

With resources stretched, a strong, data-driven case needs to be made that investment in digital transformation and AI in education builds skills that improve lives and livelihoods over the long term, especially for disadvantaged groups. But assessing the returns on this investment is complicated by the rapidly evolving capabilities of AI and by how widely economies and labour markets vary. Existing data sources are blind to the impacts of AI on informal jobs, even though more than half of young workers worldwide are engaged in informal employment (ILO, 2024).

Decades of research drawing on well-established instruments has thoroughly documented the benefits of literacy and numeracy skills for earnings, health, and society at large (Hanushek and Woessmann, 2008; Hanushek et al., 2015; OECD, 2024a). Digital skills, by contrast, are still assessed mainly through self-assessment, with AI skills representing the newest and least assessed frontier. The 2029 cycle of the OECD

Programme for International Student Assessment (PISA) will introduce a Media and Artificial Intelligence Literacy domain, but this will assess only whether 15-year-olds can critically judge AI-generated content, and its results won't be published until 2031 (OECD, 2026e).

This UNESCO report supports Sustainable Development Goals (SDGs) 4 (quality education) and 8 (decent work and economic growth). It seeks to define the state of existing knowledge about the socio-economic returns on investment in digital transformation and AI in education. The report starts with the closest available measure: the extent to which learners have acquired digital and AI skills, as well as the evidence on what these skills are worth and the methods used to produce it.

The report's main finding is a paradox. Investment is often tracked and measured precisely. But the returns are either forecast or estimated from stand-ins rather than observed. Qualifications stand in for skills, programme enrolment for skill acquisition, the skills listed in job advertisements for those actually used at work, and advertised wages for realised earnings. On its own, each of these proxies is reasonable. But taken together, they often mean that the question of whether skills are actually being acquired, used, and benefiting learners is not being measured accurately. This means that investment in digital and AI skills lacks a firm evidence base on outcomes to support and guide it.

Key Findings:

1. **Digitalization drives growth, but education's contribution cannot yet be isolated.**
   Connectivity is linked to measurable gains in GDP per capita, especially in low-income economies (ITU, 2025). But these gains reflect digitalization across the whole economy, not just education, and the largest figures attributed to digital and AI investment are projections rather than observed outcomes. Investment in digital skills is often embedded in broader national digital programmes and strategies, so its returns cannot be traced separately. And while the costs of digital transformation in education have been modelled in detail, its returns in learning and skills have not (UNESCO, 2023a).

2. **The labour market rewards advanced digital and AI skills, especially when combined with knowledge of a specific field, strong human skills, and ongoing learning.**
   Basic digital skills are now a requirement, not an advantage, while a narrow group of jobs combining GenAI literacy with domain expertise receive pay premiums of up to 36% (Martins-Neto et al., 2026). Employers worldwide rank human skills such as analytical thinking and resilience among the most essential, and workers who combine strong human skills with frequent AI use tend to earn more (WEF, 2025a; Craig and Stewart, 2025). Because technology-specific skills lose their value fastest, these premiums reward continuous renewal, not a one-off qualification (Deming and Noray, 2020).

3. **Tackling deep wealth and gender disparities in digital skills is an economic priority, and can be done. But access to skills alone does not guarantee better livelihoods.**
   In low-income countries, 96% of people have less than basic digital skills (ITU Database). Across 50 countries with available data, the share of tertiary graduates in science, technology, engineering and mathematics (STEM) barely changed between 2011 and 2021 (UIS Database), and women make up only 28% of the workforce in tech fields (WEF and LinkedIn, 2025). As well as a matter of fairness, widening access to convert untapped talent into skilled workers is an economic priority. Perhaps surprisingly, several middle-income countries have reached gender parity in young people's programming skills – a common indicator of advanced digital skills – while some of the widest gaps are in high-income countries (HICs) (UIS Database). And amid a lack of suitable employment, skills alone don't always translate into better livelihoods: female STEM graduates in particular often fail to secure STEM jobs (ILO and OECD, 2025).

4. **Vocational and training pathways improve employment more reliably than wages, especially when they are designed well.**
   Compared with general education, technical and vocational education and training (TVET) makes people more likely to be employed but has no significant effect on wages (Kemper et al., 2026). Meanwhile, the employment

gains from youth training programmes fade faster in poorer countries (The World Bank and ILO, 2024). Available evaluations across emerging economies suggest that TVET outcomes vary substantially by programme design and labour-market context.

5. **Young people's entry into work is becoming harder, but AI's role is not yet clear.**
   Globally, about 6.1% of jobs held by people aged 15 to 29 are in occupations highly exposed to AI, many of them traditional entry points into work (ILO, 2026). The share of young adults overqualified for their jobs has risen in every country income group (ILO and OECD, 2025). Yet the rising risk of unemployment among young graduates predates large language models (OECD, 2026c), and GenAI currently only seems to be reducing job postings for exposed roles in HICs (World Bank, 2026). Young people themselves are often optimistic: in a survey across more than 65 countries, close to 80% expected AI to improve their education, even as they sometimes struggled to access it (Restless Development, Makerere University and University of Cambridge, 2026).

6. **Well-being and job quality are part of the return on investment in digital and AI skills, but they are barely measured.**
   Workers who use AI report better performance, yet worry about their job security (OECD, 2023d), while employees strongly dislike being managed by algorithms (Gonzalez Vazquez et al., 2025). Problematic social media use (for example, addiction-like behaviour such as being unable to control use) rose from 7% to 11% among adolescents in Europe, central Asia and Canada between 2018 and 2022 (WHO, 2024a), and AI is being adopted in education faster than it can be governed: only 6% of teachers say existing AI policies give them clear guidance (WEF, 2026). Existing surveys treat technology as something people are exposed to, not as an investment whose effect on well-being can be evaluated, so a framework that counts only earnings and employment will overstate the return.

The message is clear: as governments, industry, and others step up investment in digital transformation and AI in education, measurement should be built in from the start. Measurement should be understood not as an additional governance requirement but as an enabler of better investment, innovation and implementation in education. Better evidence helps direct resources to the education and training approaches that most effectively build skills for work, preparing young people to enter the workforce and helping workers perform and adapt once they are in it. It is also a precondition for a trusted approach to AI in education: learners, educators and employers will only have confidence in these investments if their effects on skills, fairness, job quality and well-being are tracked transparently. Measurement needs to be comprehensive and fair across gender and socio-economic background, and flexible enough to reflect national and local priorities.

No single actor can do this alone. Collaboration across education, business, government and civil society will be essential to help young people develop the capacities they need to reach their full potential, and to ensure that those already at a disadvantage are not left behind: especially young people in low-income settings, those in informal work, and groups under-represented in tech. If investment in digital skills is targeted towards what works best – guided by solid evidence and with all kinds of people in mind – learners, workers, employers and policymakers from diverse global contexts can reap the benefits of greater economic productivity, job satisfaction and societal well-being.



Introduction

Context

Advances in artificial intelligence (AI), together with automation and digital infrastructure, are driving a structural transformation of labour markets far beyond previous industrial transitions. Earlier waves of automation, from the mechanization of agriculture to the computing revolution of the 1980s and 1990s, mainly displaced physical, routine or low-skilled tasks (Frey and Osborne, 2017). The current wave reaches further, affecting cognitive, non-routine and high-skilled work simultaneously (Eloundou et al., 2023). The economic stakes are substantial: digitalization efforts are already associated with measurable gains in GDP per capita, and projections of AI's future contribution to the global economy run into the trillions of dollars (Section 2).

The speed of digital and AI diffusion is also unprecedented. Historically, new technologies took decades to spread: across 166 countries over two centuries, countries adopted major technologies on average 45 years after their invention, although each new generation of technology has spread faster than the last (Comin and Hobijn, 2010). Generative AI (GenAI) has supercharged this pattern, being adopted faster than both the personal computer and the internet (Bick et al., 2024). Within two years of ChatGPT's launch in November 2022, GenAI tools as a whole had been used by more than half a billion people in more than 200 countries (World Bank, 2025).

But adoption across economies is uneven, determining who benefits and who misses out. By early 2024, middle-income economies accounted for more than half of global GenAI traffic, reflecting a much higher level of adoption than their GDP would predict, while low-income economies accounted for less than 1% (Liu and Wang, 2024). The share of GenAI-users among people already using the internet further indicates a sharp disparity between richer and poorer countries. By mid-2025, around 24% of internet users in HICs used ChatGPT, compared with 5.8% in upper-middle-income countries (UMICs), 4.7% in low-middle-income countries (LMICs) and just 0.7% in low-income countries (LICs) (Liu et al., 2025). Because far fewer people are online in LICs, the gap across whole populations is wider still. These gaps carry economic weight: the same long-run evidence on technology diffusion shows countries that are slower to adopt new technologies subsequently report lower income per person. The speed of adoption accounts for at least a quarter of the difference in earnings (Comin and Hobijn, 2010).

Exposure to AI follows the same unequal pattern, particularly affecting wealthier economies and roles once insulated from automation. Exposure measures how far AI could perform tasks within a job, not how many jobs will be lost from AI implementation. Around 60% of jobs in advanced economies are exposed to AI, compared with 40% in emerging markets and 26% in low-income countries and territories. Within economies, exposure is concentrated in cognitive, professional and service-sector roles, eroding the "skills shelter" that higher education once provided. However, highly-educated workers are also best-placed to move into roles that AI complements (Cazzaniga et al., 2024). The outcome for learners depends less on the qualification itself than whether it is combined with adaptable human, domain and AI skills (Section 3).

AI can affect tasks across the entire skill spectrum, especially the entry-level roles through which young people often start their careers, but the exact impact remains unclear. Globally, youth unemployment rose to 12.4% in 2025. About 6.1% of jobs held by people aged 15 to 29 are in occupations highly exposed to AI, many of them the clerical, administrative and service roles that have traditionally served as entry points into work (ILO, 2026). Yet across OECD countries, unemployment risk for young graduates began to rise before the spread of large language models, and current evidence doesn't show that AI has significantly increased it (OECD, 2026c).

Education should therefore be regarded not as a silver bullet but a lever for inclusive growth: both within and across economies. Each of the above trends points back to skills: the speed of change demands that education systems adapt, uneven adoption demands wider access, exposure demands complementary skills, and young people need pathways into work. This report sets out to examine whether existing investment in digital transformation and AI in education is effectively building these skills, and reaching those who need to access them the most.

Purpose, scope and structure

At the heart of this report is a simple question: does investment in digital transformation and AI in education pay off economically and socially, and for whom? Answering this question directly is not yet possible, since few studies follow the money from investment through to outcomes. This report therefore approaches the question through examining the outcome that investment is directly meant to produce: the digital and AI skills people acquire. It explores whether these skills lead to better employment, earnings and job quality, and to wider benefits such as well-being and civic participation, paying particular attention to whether those benefits reach the people with least access to skills. Alongside the evidence itself, the report assesses the methods used to generate it, asking how far they can support the claims made for digital and AI skills. Box 1 sets out the chain from investment to outcomes followed by the report.

Box 1. From investment to outcomes

Investment in digital transformation and AI in education is expected to pay off through a chain of consecutive steps. Each is examined in a different part of this report.

1. Investment and provision: public, private and donor spending on digital transformation and AI in education, and what it buys (Section 2).

2. Skills acquired: the digital, AI and human skills that learners actually gain, in formal education and beyond (Section 3).

3. Labour-market outcomes: employment, earnings and job quality. These depend not only on skills but on whether suitable jobs exist, how employers use AI and the barriers that stop people from securing work (Sections 3 and 4).

4. Wider returns: private gains to individuals, fiscal returns to governments through higher tax revenue and lower spending on transfers and social benefits such as well-being and civic participation. The report examines the private and social returns to investment in digital skills (Sections 2 to 4); no evidence yet exists for fiscal returns.

This report is the first part of a collaborative project between UNESCO and KPMG International measuring the socio-economic impact of investing in digital transformation and AI in education (see Box 2). The report supports Sustainable Development Goals (SDGs) 4 (quality education) and 8 (decent work and economic growth). Its scope is defined in three ways. Returns are measured in socio-economic, not pedagogical, terms: the effectiveness of technology in improving learning is outside its scope, except where learning outcomes serve as evidence of skills. The focus is the future world of work and the skills required for inclusive growth and decent employment, as defined by SDG 8. And the report pays particular attention to whether the returns reach those with least access, with gender, country income group, and formal versus informal employment as the main lenses.

Box 2. A phased approach

The project is structured around three key phases, with the first part of Phase 1 corresponding to this report.

Phase 1. Literature review and youth consultation: map and synthesize existing evidence on how public and private investments in digital and AI skills affect education, skills development, employment, earnings, and broader development outcomes, especially among disadvantaged groups. It surveys the methodologies currently used to measure these impacts and their limitations. Phase 1 will also include a structured youth consultation to capture the perspectives, experiences and priorities of young people.

Phase 2 (Proposed). Pilot empirical research: test the selected methodology/ies through a small-scale empirical study. The aim will be to assess whether the proposed approach can generate credible and useful evidence on the impact of AI and digital investments in specific countries and contexts, and to signpost implementation challenges.

Phase 3 (Proposed). Dissemination and scale-up: publish the key findings from the empirical research and disseminate them to relevant stakeholders, thereby encouraging best practice in funding and measuring high-impact digital skills education. This phase will also oversee the second round of implementation, informed by the lessons learned from the pilot, to refine and strengthen the methodology in practice.



The macroeconomic case for digital investment and its limits

The evidence: digital investment boosts growth and earnings, but the role of education is unclear

The macroeconomic case for digital investment is founded on connectivity and economy-wide digitalization, where the evidence is robust. Panel data from up to 139 countries between 2010 and 2023 indicate that a 10% increase in fixed broadband penetration is associated with a 1.59% rise in GDP per capita, while a 10% increase in unique mobile broadband penetration is associated with a 2.29% increase, with a greater impact in low-income economies (ITU, 2025).

Massive investment in AI has raised expectations of large economic gains, though their scale remains largely speculative. Total corporate investment in AI reached US$252.3 billion in 2024, with private investment growing by 44.5% year-on-year (Maslej et al., 2025). Estimates of the economic payoff vary widely, partly because they measure different things. In an upside scenario in which faster AI adoption delivers stronger productivity gains than currently expected, global total factor productivity (a measure of how efficiently an economy combines workers and capital to produce output) would be 0.8% higher by 2035, with larger gains in countries better prepared for AI adoption (IMF, 2025). Other estimates are far larger: the cumulative effect of investment in AI solutions and services (counting both the spending itself and the activity it generates) is projected at US$22.3 trillion by 2030, about 3.7% of global GDP (IDC, 2025).

Resources for education, by contrast, are barely growing. Total global spending on education by governments, households and donors combined reached about US$5.8 trillion in 2022. Once inflation is taken into account, it grew by only 1.8% a year between 2010 and 2022, lagging behind the rate of expansion of the global economy (The World Bank and UNESCO, 2024). External funding for education in low- and middle-income countries provided by donors, international organizations and development banks is projected to fall by between 25% and 30% between 2023 and 2027 (UNESCO, 2026d). Within these totals, global figures do not separately identify how much has been or will be invested in digital transformation and AI in education.

The clearest example of a major, deliberate and traceable public commitment to digital investment is that of the European Union (EU). Under the Recovery and Resilience Facility (RRF), every national recovery plan following the COVID-19 pandemic was required to allocate at least 20% of its budget to the digital transition of the country's economy and society, including an estimated EUR 28.3 billion for digital skills and education (UNESCO, 2026b; European Union, 2021). The returns are projected through economic modelling, not measured: the EUR 148.8 billion earmarked for the digital transition is expected to generate EUR 302.3 billion in economic activity by 2030, and existing monitoring cannot yet confirm whether these gains are materialising. Of the four areas modelled (digital skills, digital infrastructure, and the digitalization of businesses as well as public services), digital skills is projected to deliver the highest return, with EUR 23.6 billion generating EUR 42.6 billion in economic output within the EU (European Commission, 2026). However, this only captures the economic activity generated by spending on digital skills, not the return to the skills learners actually acquire.

Elsewhere, investment in digital skills is rarely identified separately within broader digital programmes, making its returns even harder to trace. The African Union's Digital Transformation Strategy aims to digitally empower every individual, business and government on the continent by 2030, but does not single out a dedicated budget for skills (African Union, 2020). India's Digital India and Skill India programmes underpin one of the largest skilling initiatives worldwide, including rural digital literacy campaigns; the country's digital economy now contributes up to 14% of GDP, though the share attributable to digital skills is not identified (Government of India, 2026). In the Pacific, investment flows almost entirely through externally financed initiatives: between 2007 and 2019, roughly US$650 million was allocated to more than 220 ICT and e-government capacity projects, with skills development folded into wider project objectives (UNESCO, 2024a).

For education specifically, the costs of digital transformation are better documented than its returns. UNESCO has recently developed three increasingly ambitious scenarios to estimate these costs: basic offline learning, in which schools have electricity and shared devices but no internet; fully connected schools, in which schools also have internet; and fully connected schools and homes, in which internet, electricity and devices also reach students' homes. For low-income countries to reach basic offline learning and low-middle-income countries to fully connect their

schools between 2024 and 2030, they would need US$33 billion a year in combined capital and operating costs, raising their existing financing gap for national SDG 4 benchmarks by 50%. Meanwhile, even the basic offline scenario would cost US$67 billion in capital expenditure globally (UNESCO, 2023a; Yao et al., 2021). No equivalent modelling exists of what these different levels of investment would return in terms of learning and skills.

For education more broadly, from school to tertiary level, a robust body of evidence exists on return to individuals, governments and society. Private returns to individuals are the best documented: across 165 countries, each additional year of schooling raises earnings by around 8% to 10% (Patrinos, 2024; Montenegro and Patrinos, 2023; Psacharopoulos and Patrinos, 2018).

Fiscal returns to governments come through higher tax revenue and lower welfare spending, but are estimated far less often: the most recent estimates, for OECD countries, show the public net financial return from tertiary education over a graduate's working life is higher for men (about US$127,000) than for women (about US$60,600) (OECD, 2021). Social returns accrue to society as a whole through lower crime (Lochner and Moretti, 2004; Machin and Sandi, 2025; UNESCO, 2026a), greater civic participation (Dee, 2004; Le and Nguyen, 2021) and compounding intergenerational mobility effects (Heckman et al., 2006). By contrast, no comparable body of evidence yet exists for investment in digital and AI skills education, with the little data available mainly dealing with individual returns.

The methodological limitations: attribution, projection and a conceptual gap

Three limitations separate the evidence above from any firm conclusion about the returns on investment in digital transformation and AI in education:

The first is attribution, which applies to both spending and returns. On the spending side, global education finance data do not show how much is invested in digital transformation and AI in education, so the investment itself is largely untraceable outside dedicated programmes such as the EU's Recovery and Resilience Facility (RRF). On the returns side, the macroeconomic gains reflect the combined effects of digitalization across the entire economy – commerce, healthcare, governance and education alike – making it impossible to isolate education's specific contribution (OECD, 2023e; Bulman and Fairlie, 2016). Nor is there anything in the panel-data or composite-index literature that identifies the education channel separately. Because connectivity serves every sector at once, more data alone would not solve this: isolating education's contribution would require studies designed specifically to separate it from that of other sectors.

The second is the gap between projected and actual returns. The EUR 302.3 billion attributed to EU digital recovery investment and the projections of AI's contribution to the global economy are modelled estimates, not observed outcomes. Their credibility depends on assumptions that are rarely tested with the rigour routinely applied to estimates of the returns to schooling; checking them after the fact is usually impossible. In the case of the EU, the European Court of Auditors found that the indicators used to track the RRF's digital spending are too broad, focus mostly on outputs, and are not well aligned with the EU's own digital strategy: all of which significantly limits how far the funding's contribution to the digital transition can be measured (ECA, 2025).

The third and most fundamental limitation is conceptual. Despite the scale of investments in digital education, there is no widely accepted framework or methodological consensus for capturing their socio-economic returns. Instead, there is a fragmented set of proxy indicators covering learning outcomes, skills attainment and labour market results. This absence is not merely due to limited empirical evidence. Traditional approaches in the economics of education evaluate relatively stable investments – such as additional years of schooling or educational attainment – whose expected outcomes are measurable using widely accepted indicators (see Table 1). Digital transformation offers no equivalent: the investment is a continuum, not a discrete unit, and the outcomes it is expected to produce span learning, labour market, equity and efficiency, and extend to public life and learners' ability to use AI responsibly and make ethical judgements about it (UNESCO, 2021; UNESCO, 2024c; WEF, 2025a).

Because the returns on investment in digital transformation and AI in education cannot be isolated at the macroeconomic level, Section 3 turns to the closest available measure: the skills this investment is meant to build, and what they are worth in the labour market.



The value of skills in a changing labour market

Skills development and attainment represent the dimension where the socio-economic rationale for investment is most direct (OECD, 2026a; The World Bank, UNESCO and ILO, 2023; UNDP, 2019). If young people don't acquire the digital skills necessary to participate in the modern economy and society, they won't be able to translate these into earnings, employment, and community. This will in turn lead to those who are already disadvantaged being left further behind. This dimension is also where pressure from AI-driven labour market restructuring is most acute (WEF, 2025a; Gmyrek et al., 2025).

This section focuses on the economic returns from skills and distinguishes the evidence from the methods used to obtain it. The evidence is divided into two aspects: demand (what employers value and reward) and supply (the skills possessed by the working-age population, and the pathways through which they are developed).

The evidence from the demand side: employers value depth over familiarity

Three kinds of measurement have traditionally quantified the returns to digital skills, each examining the labour market from a different perspective (see Table 2):

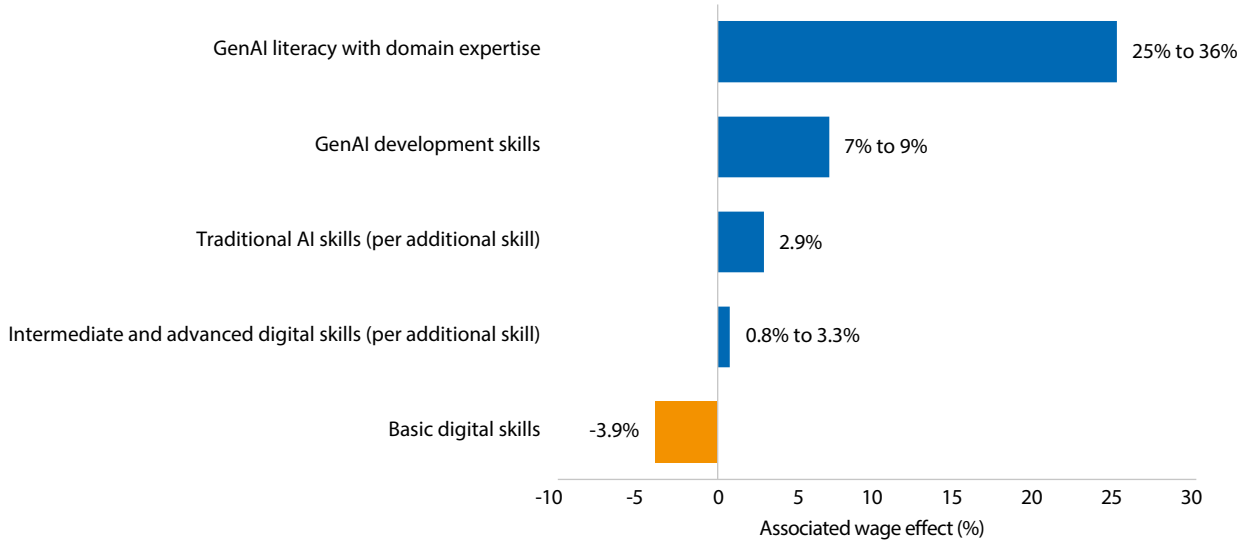
- **Direct skills assessments** have established that tested ICT proficiency is linked to substantially higher wages, but provides only indirect evidence of employer demand for these skills (Langer and Wiederhold, 2023; Falck et al., 2021; Grundke et al., 2018).
- **Studies that analyse the bundles of skills listed in job adverts** – rather than individual skills in isolation –can help explain why otherwise similar jobs pay differently. However, such studies are so far limited to single countries (Deming and Kahn, 2018; Ziegler, 2024).
- **Vacancy-based estimates have been used to calculate the premiums on digital and AI skills**, but until recently these have been confined to single sectors or the United States job market as a whole (Garcia-Lazaro et al., 2025; Lightcast, 2025).

Demand for digital skills is near-universal but stratified. The most comprehensive wage-premium analysis to date examined more than 67 million job postings across 29 low- and middle-income countries (LMICs) and high-income countries (HICs) from 2021 to 2024 (Martins-Neto et al., 2026). Across both, approximately 47% of postings required at least one digital skill, while intermediate skills such as industry-specific software and advanced skills such as programming and data analysis were particularly prized. Explicitly AI-related skills remain rare –appearing in about 1% of postings in HICs and even fewer in LMICs – but represent the fastest-growing segment of demand.

These differences are reflected in wage returns. Across both LMICs and HICs, jobs requiring only basic digital skills such as email and word processing (concentrated in routine clerical roles themselves under pressure from automation) paid almost 4% less than those requiring none. Put another way, basic digital skills have become a floor, not a differentiator. Above that floor, each additional technical skill adds around 0.8% to wages in HICs and roughly 3% in emerging economies. But the biggest gains – between 25% and 36% – go to workers who combine generative AI (GenAI) literacy with domain expertise in fields such as marketing and finance (see Figure 1). These premiums apply to a small share of jobs, since AI-related skills appear in only about 1% of postings. Nevertheless, they show where skills demand is heading. For example, within the education sector itself, the concentration of AI-related jobs and workers with AI skills nearly tripled between 2016 and 2024: second only to the technology, information and media sector (WEF, 2026).

Figure 1. The wage returns to digital and AI skills form a steep gradient

Associated wage effects of digital and AI skill requirements in online job postings, 29 countries, 2021-2024



Note: Units differ across categories: basic digital skills are measured per posting; intermediate, advanced and traditional AI skills per additional skill listed; the GenAI development premium is additional to the returns to traditional AI skills. Estimates are associations based on posted wages, not causal effects on realized earnings.
Source: Author's analysis based on Martins-Neto et al., 2026.

Broader human skills remain important, and shape which workers benefit from AI. In a survey of more than 1,000 employers across 55 economies, seven in ten considered analytical thinking a core skill for their employees, followed by resilience, flexibility and agility (67%), leadership and social influence (61%) and creative thinking (57%). Meanwhile, fewer than half said familiarity with AI or big data were essential (WEF, 2025a). Job vacancy data points the same way: across 10 OECD countries, over 50% of vacancies in occupations highly exposed to AI required at least one social, emotional or digital skill (OECD, 2024c). Yet these skills are often left out of job advertisements – perhaps because they are typically assessed at the interview rather than the application stage – making them hard to see in hiring data (WEF, 2025b).

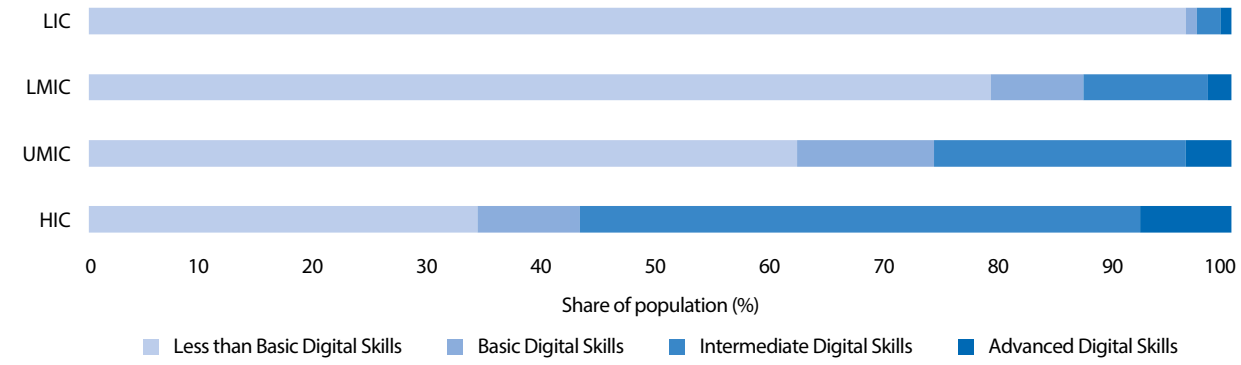
Evidence linking human skills to earnings and AI use is scarcer. One UK study assessed more than 2,000 working adults against the Skills Builder Universal Framework, which covers eight core transferable skills including problem-solving, creativity, teamwork and leadership. Workers in the top quarter of these skills earned roughly 9% to 15% more than those in the bottom quarter (equivalent to additional earnings of up to GBP 6,100) and were 44% less likely to be unemployed, even after accounting for education, age, region and job type. They were also 30% more likely to use AI at work. Frequent AI users earned GBP 8,300 a year more than non-users with the same skill level, and workers who combined strong human skills with frequent AI use earned at least 53% more than the other groups in the study (Craig and Stewart, 2025; Ravenscroft, 2026). However, these are associations, not necessarily causal effects: workers who are already more skilled or better paid may simply be more likely to use AI.

The evidence from the supply side: digital skills skew towards young men in wealthy countries

Digital skills are distributed extremely unevenly between richer and poorer economies. An estimated 96% of the population in low-income countries (LICs) have less-than-basic digital skills. The same is true of 62% of the population in upper-middle-income countries and 34% in HICs. Meanwhile, only 3% of people in LICs and 13% in LMICs have intermediate or advanced skills, compared with 57% in HICs (see Figure 2).

Figure 2. Large disparities in digital skills persist across country income groups

Distribution of the population by digital skills level and country income classification (%), 2023

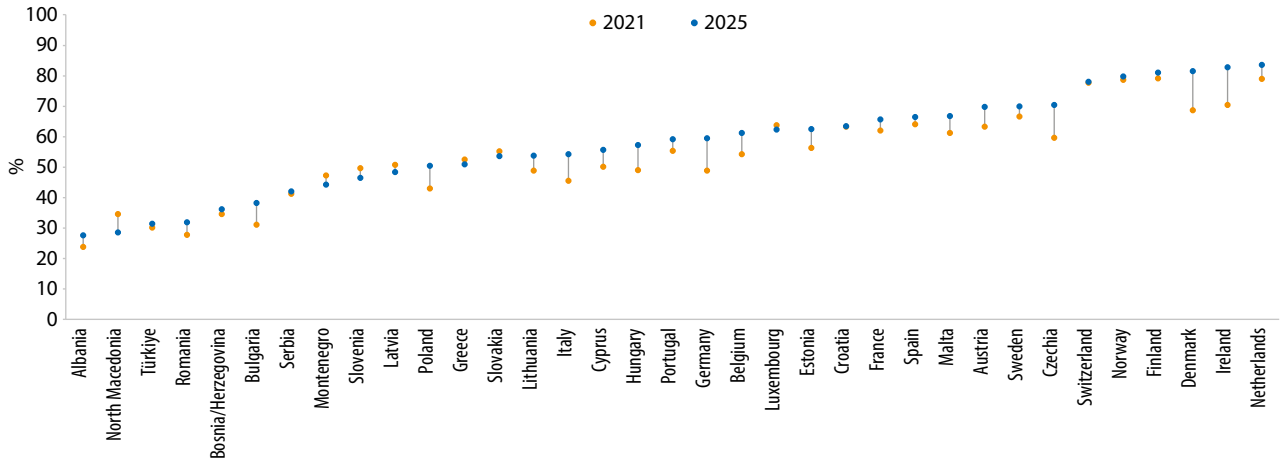


Note: Basic digital skills refer to the use of digital devices, email, web search and online transactions; intermediate to software and data management; advanced to data analysis, software development and high-level computing competencies. *Source*: ITU Database.

Meanwhile, the European Union aims for 80% of adults to possess at least basic digital skills by 2030 (European Union, 2022). However, progress has been uneven: several countries recorded slight declines in recent years, and others only marginal gains (see Figure 3).

Figure 3. Basic or above-basic digital skills have improved slowly across Europe

16- to 74-year-olds with basic or above overall digital skills, selected countries, 2021 and 2025

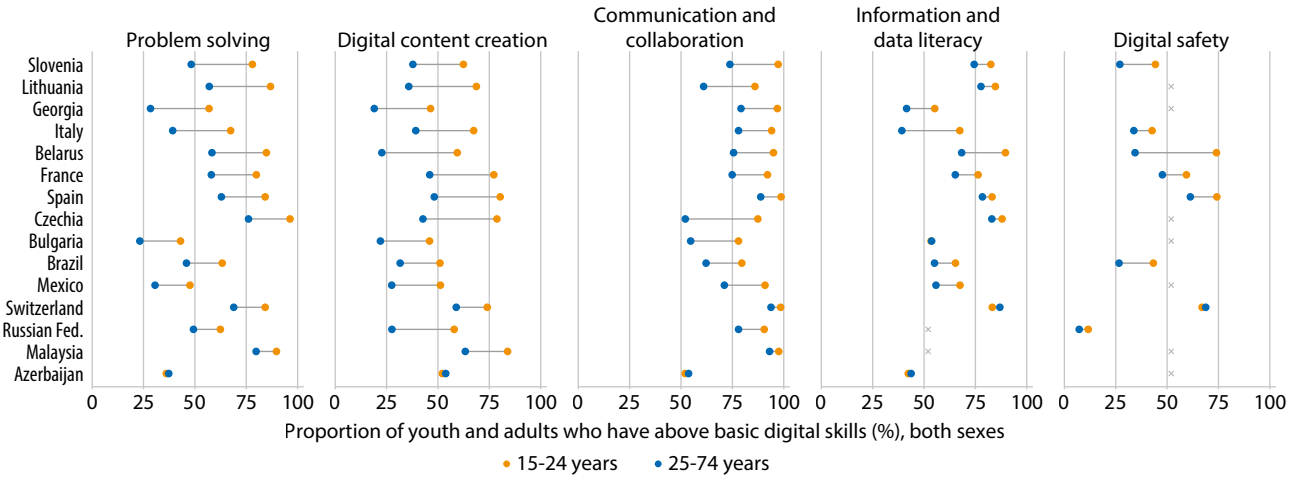


Note: Based on the European Commission's composite Digital Skills Indicator, derived from the EU survey on ICT use by households and individuals; it maps self-reported activities against the DigComp Framework and captures 12 of its 21 competences. *Source*: Eurostat, 2026a.

Younger people are more likely to have strong digital skills. Across the fifteen countries reporting comparable data, 15- to 24-year-olds were more likely to attain above-basic proficiency in almost every domain of digital skills (see Figure 4). This advantage is greatest in problem-solving and digital content creation, narrowing considerably in communication and collaboration, as well as in information and data literacy. The data suggest that being a "digital native" is not a uniform skills profile: in most countries surveyed young people are not markedly more likely to possess the "soft" skills most relevant to navigating an information environment shaped by AI.

Figure 4. Young people report higher digital skills proficiency than the broader adult population

Proportion of 15-24-year-olds and 25-74-year-olds with above-basic digital skills, by skills domain, selected countries, 2023

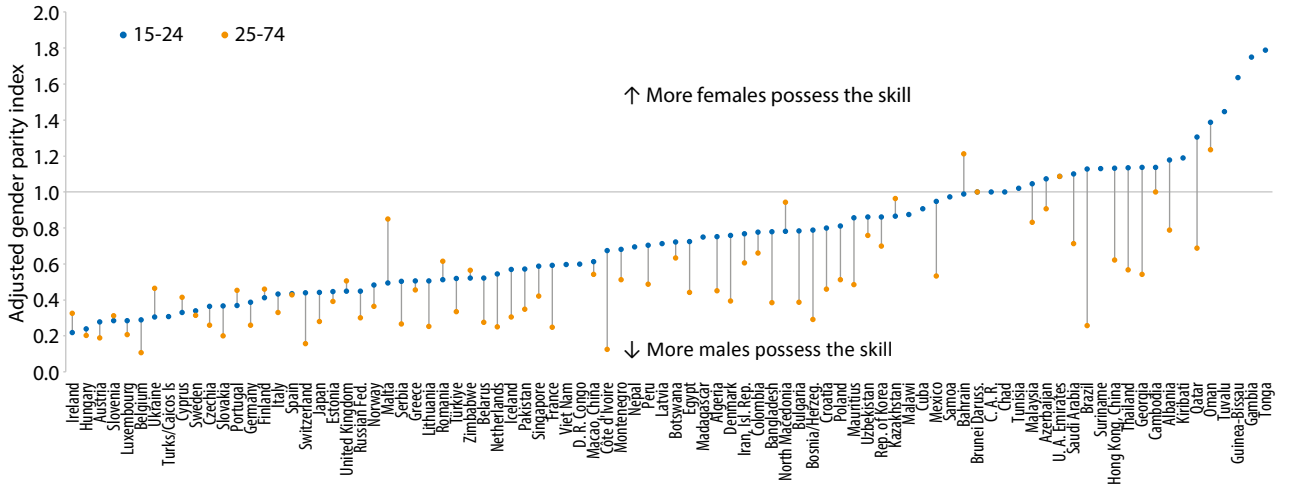


Note: The five domains correspond to the competence areas of the European Digital Competence Framework (DigComp). A grey × indicates that the country does not report that indicator. *Source*: UIS Database.

Women face severe shortfalls in advanced digital skills. The widest gender gaps in programming are found in several high-income European countries. By contrast, several middle-income countries have reached or exceeded parity (see Figure 5). Programming is used here as an example of advanced digital skills, because it is one of the few such skills measured consistently across countries. As AI tools increasingly generate code, the labour-market value of programming itself may change, but the gap still signals unequal access to advanced digital learning.

Figure 5. Gender disparities in programming skills remain substantial across countries

Adjusted gender parity index for programming skills, youth (15-24) vs adults (25-74). Values below 1 = more males possess the skill.



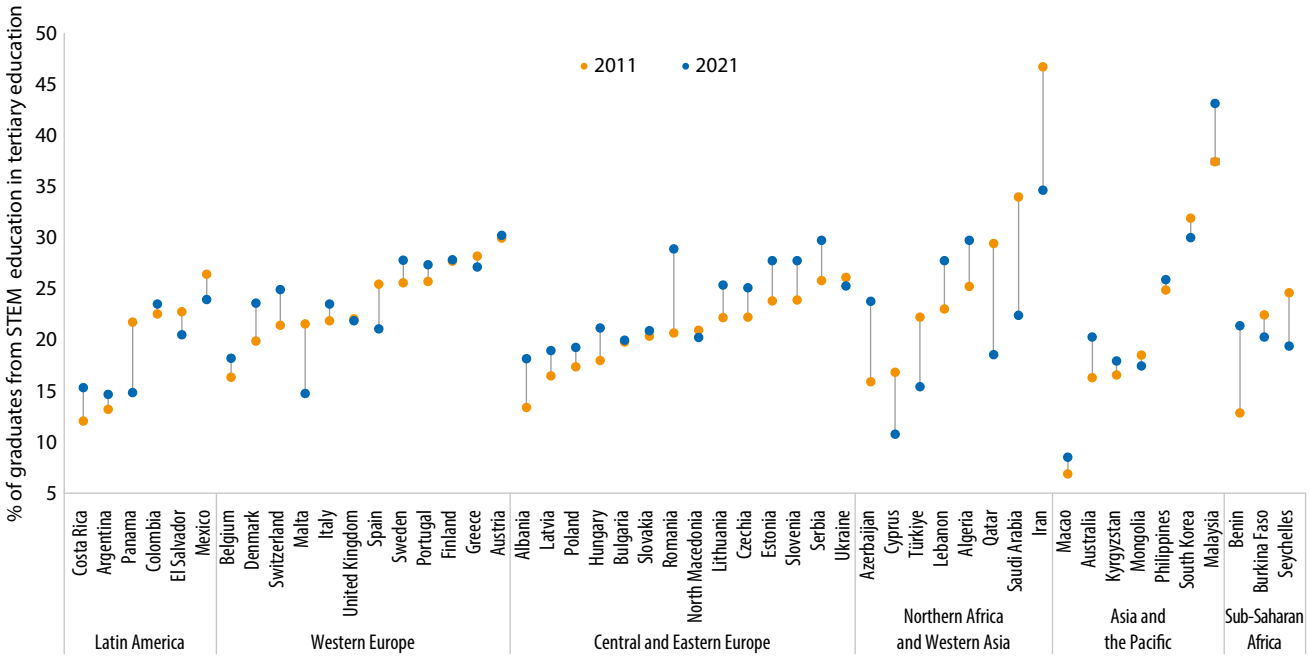
Source: UIS Database.

The evidence from the supply side: not enough digitally skilled workers are graduating

The supply of tech-capable workers has remained static. Within formal education, science, technology, engineering and mathematics (STEM) represent the pathway most explicitly oriented towards the skills rewarded by technology-intensive labour markets. Yet across 50 countries with available data, the proportion of tertiary graduates from STEM fields grew only marginally between 2011 and 2021, from 22.8% to 23.1%. In roughly three-quarters of countries, the share of STEM graduates barely shifted in either direction, growing or shrinking by less than five percentage points in the same period (see Figure 6).

Figure 6. The share of STEM graduates has barely changed in a decade

Share of graduates from STEM in tertiary education, 2011 vs 2021



Source: UIS Database.

For those who do enter the field, the returns are substantial. Across OECD countries, STEM graduates generally receive the highest earnings. In the United States, a tertiary STEM qualification is associated with earnings up to 20% above the national average (OECD, 2025). Occupation-based data corroborate this: US workers in non-STEM occupations earn approximately 28% less, a gap that persists at every level of educational attainment (U.S. National Center for Science and Engineering Statistics, 2026).

However, the gains from STEM jobs are largely captured by men. Whether STEM employment narrows the gender pay gap remains contested (Jiang, 2021; US Census Bureau, 2021; Michelmore and Sassler, 2016), but few women are positioned to benefit either way. According to LinkedIn's global member data, women's representation in tech fields increased only marginally between 2016 and 2024, rising from 26% to 28%. The gap widens with seniority: as of 2025, women held only 24% of STEM managerial positions and just 12% of STEM C-suite roles (WEF and LinkedIn, 2025). Similarly, across 27 countries surveyed, women occupy 38.5% of director-level positions, but only 31.2% of AI leadership roles and 13% of C-suite positions in AI firms (LinkedIn Economic Graph Research Institute, 2026). This could reflect difficulties in entering relevant fields to begin with: women accounted for 35.5% of STEM graduates in 2017 but only 29.6% of STEM job entrants the following year, a drop-off repeated in every cohort up to 2021 (WEF and LinkedIn, 2025).

The evidence on STEM also warns against treating technical competencies as permanent assets. One analysis of job postings between 2007 and 2019 shows how, as occupational skill requirements evolve, technology-specific skills become obsolete more rapidly, so the early pay advantage they bring shrinks as workers get older. Computer science and engineering graduates earn approximately 45% more than other STEM graduates early in their careers, but this premium diminishes over time. In contrast, graduates from broader scientific disciplines experience smaller initial returns compared to non-STEM graduates, but that advantage grows as they progress in their career. The proportion of applied STEM graduates working in STEM occupations also decreases, from 89% at age 24 to 71% by age 35 (Deming and Noray, 2020).

In TVET, the pathway explicitly designed to lead to employment, the integration of digital technologies and AI has only just begun (see Table 3) and returns so far are uneven. The most comprehensive recent review of TVET to date – drawing on 39 studies from 1990 to 2022 – finds that compared to general academic education, vocational training makes people about five percentage points more likely to be employed, but does not significantly affect their wages. When measured against people who received no further training at all, the employment advantage rises to nearly 12 percentage points and wages improve substantially (Kemper et al., 2026).

The returns to TVET depend heavily on how programmes are designed and on the labour markets graduates enter. Evidence from 19 emerging economies shows how widely results vary. In Mongolia, an oversubscribed vocational programme increased paid employment by just 4%, but boosted women's earnings by 13%. In Türkiye, large-scale certified vocational courses had no average employment impact after three years. In Egypt, graduates of vocational secondary education earned little more than people with no formal education. This variation persists even in the most rigorous studies evaluating TVET programmes (The World Bank, UNESCO and ILO, 2023), suggesting that what matters is not whether TVET is offered but how well it is designed and matches local demand for skills.

Finding a job is only part of the picture; the quality of that job matters too. Of more than 1,600 Mozambican TVET graduates tracked over their first 11 months in the labour market, 51% had found work, but only around 9% secured a "good job" characterized by decent pay and a formal contract, with even lower rates among women in particular (Jones et al., 2021). This reflects the limited supply of formal jobs as much as the training itself, and it shows why measuring employment rates alone can hide how much graduates actually gain from skills programmes.

Beyond formal qualifications, targeted training schemes show modest but real benefits. A review of 228 youth-focused training programmes across 62 countries found small average gains in employment and earnings. Costs vary widely, between US$230 and US$1,700 per participant, but most cost-benefit analyses suggest the long-term returns justify the outlay. Three patterns stand out from the literature. First, durability varies by country: in poorer countries, the employment gains fade within a year; in richer ones, they grow over time. Second, the benefits of training are largest for women, under-25s, and lower-skilled workers (The World Bank and ILO, 2024). Third, vocational graduates tend to enter work faster than those from general academic programmes at the same level. But this head-start eventually disappears as workers age, partly because TVET's narrower focus makes it harder to retrain (Hanushek et al., 2017; Hampf and Woessmann, 2016; OECD, 2020). A randomised trial in Colombia illustrates the trade-off: technically trained graduates found jobs faster, while those who received more socio-emotional training caught up rapidly and stayed in their jobs for longer (Barrera-Osorio et al., 2020).

None of the evaluations above tested digitally-integrated TVET, which is too recent to have been evaluated at scale. What they show is that the returns to vocational pathways are contingent on programme design, the quality of training and labour-market demand rather than guaranteed by provision. This makes the current situation on digital and AI integration in TVET across the global education landscape more striking: policy has advanced well beyond the available evidence. Strategies, frameworks, and initiatives now encompass every level of governance (see Table 4), yet the impact of these efforts on skills development, employment or earnings remains largely unquantified. The existing empirical evidence is almost exclusively at the institutional level and focuses on learning outcomes rather than labour market results (OECD, 2026b).

The evidence on matching supply and demand: skills and qualifications are rewarded separately, and young people's digital capabilities are recognised the least

The returns reported thus far are based on qualifications as a proxy for skills: a measure that is too coarse to capture quality, variation within credentials or comparison across countries. One instrument removes this assumption and reframes the evidence presented above. The OECD's Survey of Adult Skills (PIAAC) directly assessed the foundational information-processing skills of approximately 160,000 adults aged 16 to 65 across 31 countries and economies in 2023 (see Table 5). These skills – literacy, numeracy and adaptive problem-solving – form the foundation upon which digital and AI competence is built, though not digital or AI skills in themselves (OECD, 2024a).

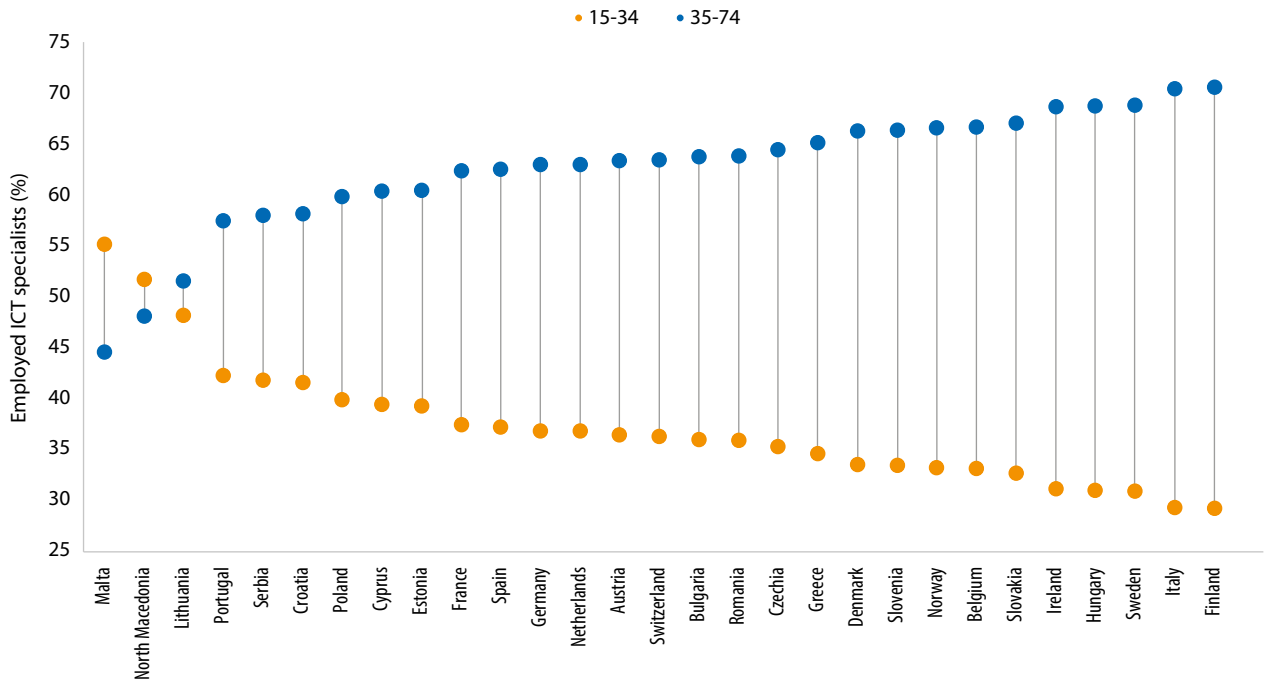
PIAAC confirms that skills and education each carry independent rewards. Adults whose numeracy scores are 58 points higher on the PIAAC scale have hourly wages about 9% higher. Separately, adults with about three more years of education have hourly wages about 16% higher. Each gain holds on its own: among people with the same level of education, those with better numeracy skills earn more, and among people with the same numeracy skills, those with more education earn more. The numeracy-wage relationship is statistically robust across 27 of the 31 countries studied. The benefits extend well beyond pay. Adults with strong numeracy are far more likely to report high life satisfaction (84% versus 65% for those with weaker skills), good health (55% versus 28%), trust in others (51% versus 25%) and volunteering (41% versus 22%). These gaps persist even after controlling for age, income and other background factors, suggesting numeracy shapes how people engage with the world, not just their earnings (OECD, 2024a).

If qualifications alone were rewarded, young people would be thriving. Instead, the labour market absorbs them the least. Between 2013 and 2023, the share of overeducated young adults aged 25-29 (those with a higher level of education than their job requires) increased in every country income group, but far more in LMICs. Among young men in HICs the change was negligible (0.4 percentage points), compared with a rise of 6.7 percentage points among young men in UMICs. Among young women, the largest rise was in LMICs and LICs, at 6.2 percentage points (ILO and OECD, 2025).

The ICT field also shows a gap between qualification and occupation among young workers. In nearly all European countries, younger workers (aged 15-34) constitute the majority of employed individuals with ICT education, yet they remain underrepresented among employed ICT specialists. Conversely, older workers occupy a disproportionately larger share of specialist positions (Figures 7 and 8). In Finland, nearly 60% of employed people with ICT education are aged 15-34, rising to 80% in Italy, yet only 30% of ICT specialists fall within this age group in both countries. This does not mean young graduates should replace experienced workers. Rather, it suggests that many young people with ICT qualifications are working outside ICT specialist roles: perhaps because of experience requirements, limited entry-level openings or the relevance of ICT skills to other occupations.

Figure 7. The ICT workforce across Europe is dominated by older age groups

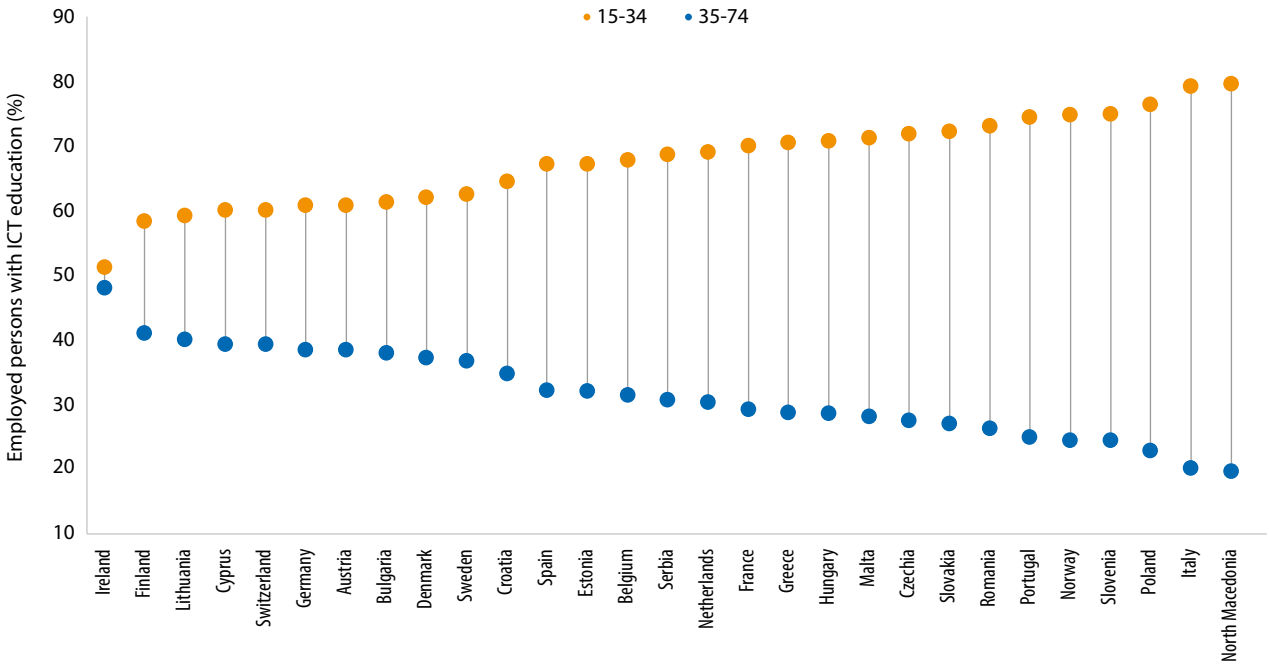
Employed ICT specialists by age, selected countries, 2025



Source: Eurostat, 2026b.

Figure 8. Young workers dominate the ICT education pipeline across Europe

Employed persons with ICT education by age, selected countries, 2025



Source: Eurostat, 2026c.

Young people are already adjusting their subject choices in response to AI. Among roughly 3,800 enrolled US students, 16% have changed their field of study because of the anticipated impact of AI, while 47% have considered it strongly or somewhat. Students in technology fields are among the most likely to say they have strongly considered switching (Gallup and Lumina Foundation, 2026). Switching may be a rational response to expected changes in employment prospects. But these decisions are being made with little evidence on how AI will affect returns to different fields, and comparable data do not yet exist outside a few high-income countries.

Optimism about the impact of AI is highest where adoption and tech skills are thinnest. A youth survey conducted across more than 65 countries, with the majority of respondents from sub-Saharan Africa and South Asia, found that around two-thirds of participants aged 18-35 use AI daily and close to 80% expect it to improve their education and learning: even while participants also identified substantial infrastructural and cost barriers to access (Restless Development, Makerere University and University of Cambridge, 2026). Meanwhile, the sharpest declines in net positivity towards AI are concentrated in Western economies. In most advanced economies, 18- to 24-year-olds present a particular anomaly: they are among the heaviest users of AI tools but report less positive than older people who use it just as often (Public First, 2026).

Methodological limitations: proxies, contested methods and an invisible majority

Four key limitations qualify the findings of this section, and they compound one another:

- **First, digital skills are predominantly measured through proxies.** The main international indicators, SDG 4.4.1 and the EU Digital Skills Indicator, are derived from household surveys in which respondents self-report whether they have undertaken specific computer-related activities (see Table 6). Measurement also faces ongoing challenges: the multidimensional nature of digital skills, comparability over time, the validity of comparisons across gender and socioeconomic status and the difficulty of keeping pace with technological advancements (UNESCO, 2023a). Furthermore, some countries are entirely excluded – for example, no Pacific Island nation formally reports data on SDG indicator 4.4.1 through any survey source (UNESCO, 2024a).
- **AI skills represent the newest and least-measured frontier.** PISA's 2029 cycle introduces an innovative new domain, Media and Artificial Intelligence Literacy (OECD, 2026e). However, it frames AI literacy not as technical proficiency in using or developing AI, but as the capacity to critically evaluate AI-generated content, understand how these systems operate and consider their ethical implications. Consequently, the assessment landscape remains devoid of a measurement of workforce-relevant AI skills from the supply side. Moreover, the results will only be available in 2031, by which time the AI skills that matter most for work and learning may have moved on from those the assessment was designed to capture.
- **National-level systems are also yet to assess AI skills on a large scale.** Instead, a body of academic instruments is emerging, such as a multinational AI literacy test administered to university students in Germany, the United Kingdom and the United States (Hornberger et al., 2025) and the online Generative AI Literacy Assessment Test (Jin et al., 2025). The closest approximation to national-scale measurement is an AI literacy module in China's annual nationwide survey of medical students (Li et al., 2026). However, this module remains sector-specific and relies largely on self-reported or brief knowledge-based items, thereby perpetuating the same proxy problem.
- **Second, estimates of AI's impact on the labour market, which increasingly influence policy decisions, vary widely with the method used and the context.** Depending on whether exposure is measured across whole occupations or individual tasks, and on the assumptions built into scenario models, estimates of the share of jobs at risk can differ hugely (Annex D). Context matters too: across 84 economies, generative AI appears to meaningfully reduce job postings for exposed roles in high-income countries. But these impacts are statistically insignificant in low- and middle-income countries, where AI adoption is still limited (World Bank, 2026).

- **Third, returns are expressed in units that do not correspond to skills.** In the TVET and active labour market policy literature, participation and completion serve as proxies for skill acquisition. In the supply-side literature, qualifications stand in for competence. In the demand-side literature, the posted requirements represent the skills actually used, and the posted wages reflect realized earnings. Each substitution is reasonable on its own, but they add up. A study may report a "return to digital skills" when what it has actually measured is the return to enrolling in a programme, being hired into a job whose advert lists those skills, and earning the advertised wage, without checking whether any skills were learned or used. PIAAC is the exception that highlights the cost of this approach: where skills are measured directly, they are shown to be valued separately from the qualifications that typically serve as proxies (OECD, 2024a).
- **Fourth, and most importantly, the entire evidence base focuses solely on the formal labour market and is blind to the experience of the majority of the world's young workers.** More than half of young workers worldwide are engaged in informal employment, and in low-income countries, three in four can expect only self-employed or temporary work (ILO, 2024). Current data sources are unable to detect whatever impact AI may be having on the informal and self-employed sectors through which most young people in developing economies actually earn a living.



Beyond employment and earnings: well-being, job quality and wider societal outcomes

Well-being and job quality are not a caveat to the returns documented in Section 3, but an essential part of them. A digital skill that raises wages but leads to work that is draining, constantly monitored or insecure delivers a smaller return than the wage figure implies. A learning tool that lifts test scores while eroding motivation or attention – skills that employers reward – may register a gain in the classroom and a loss in the labour market a decade later. No study reviewed here follows learners long enough to test this, which makes it a priority for longitudinal research.

However, effects such as civic participation or trust sit outside the investment-to-earnings chain altogether and benefit learners and societies whether or not incomes rise. This section reviews what is known about these outcomes for workers and young people now entering training and work, finding that the instruments used to measure them are far less developed than those reviewed in Section 3. The consequence for this project is direct: a framework that measures earnings and employment alone will overstate the return on digital skills, because it will not see their downsides in terms of perceived precarity, mismanagement by employers, digitally mediated strain and misuse of digital tools.

The evidence: gains and strains arrive together

Workers who use AI report that it improves their output but worry about where it will lead. The OECD's surveys of AI workers and employers find that large majorities of workers using AI say it has improved their performance and even their enjoyment of work, while employers report rising rather than falling skill needs. Yet substantial proportions of the same workers express concern about job security over the coming decade (OECD, 2023d). This ambivalence mirrors the pattern among young adults in Section 3, where the heaviest AI users are also the most uncertain about it, and suggests that positive returns and perceived precarity are being experienced by the same people at the same time.

How AI is used to manage workers matters more than whether it is used. As digitalisation makes more intense and harder to switch off from, workers whose pace is set by machines or monitored by software consistently report worse working conditions (Eurofound, 2022). The first EU-wide survey of AI in workforce management found that a third of employees already use AI at work, that digital monitoring is common, and that automated scheduling and task allocation is the most widespread form of algorithmic management. Its central finding is that a little AI management does not appear to seriously harm job quality, but full platformisation does (De Cuyper et al., 2025; Gonzalez Vazquez et al., 2025).

The cohort now entering training and work shows consistent signs of digitally mediated strain. The latest round of the Health Behaviour in School-aged Children survey, covering 44 countries, shows problematic social media use among adolescents increased from 7% to 11% between 2018 and 2022, with girls more affected than boys. Roughly one in eight showed signs of problematic gaming and one in six reported being cyberbullied (WHO, 2024a; 2024b). Nearly half of 15-year-olds reported feeling nervous or anxious when their phone is not nearby, and those students also scored lower in mathematics (OECD, 2023a). The OECD's Survey on Social and Emotional Skills situates these findings in a developmental context: 15-year-olds report substantially lower levels of curiosity, energy, trust and optimism than 10-year-olds, and girls are significantly more likely to struggle to regulate emotion and manage stress. These skills are among the strongest measured correlates of adolescent life satisfaction and test anxiety (OECD, 2024b). The OECD survey is also uniquely positioned to detect whether a tech-saturated adolescence is eroding the socio-emotional foundations that Section 3 shows are rewarded in the labour market.

AI is arriving in education faster than the capacity to govern it. Across ten low- and middle-income countries, children's most common concerns about AI are people using it to scam or deceive others (34%), to spread false information (32%), and to create fake sexual images or videos (26%). Yet in four of the ten countries, three in ten children report having no such concerns at all, and children with stronger digital skills, although more likely to use AI, are no more likely to be concerned about it (UNICEF, 2026). The risk is exacerbated by the conditions of adoption: GenAI adoption is progressing faster than institutional governance in most systems (OECD, 2026d); only 6% of teachers believe existing AI policies provide clear guidance (WEF, 2026); and the performance of AI tools is highly sensitive to their configuration (Tophel et al., 2025). Consequently, outcomes depend on decisions around how and where to deploy AI that few institutions are yet equipped to make.

The methodological limitations: technology is an exposure, not an outcome

Measurement in this area falls into three tiers (see Table 7). Student well-being is tracked by well-established international surveys, but these treat technology only as something students are exposed to (screen time, problematic use) rather than as an intervention whose effect on well-being can be evaluated. Worker well-being is covered by long-running working-conditions surveys, which have only recently begun asking about AI and algorithmic management. For broader ethical and societal outcomes, no outcome measures exist at all: what is counted are inputs, such as frameworks adopted, governance structures established and incidents reported, not whether learners or societies are better or worse off as a result.

Three gaps follow. **First, causation:** nearly every finding above is a correlation, and the link could run in reverse, with struggling young people turning to heavier technology use rather than heavy use causing them to struggle. Second, specificity: surveys measure technology use in general, not educational technology specifically, so the well-being effects of the tools actually being used in classrooms and training workshops go unmeasured even as their effects on learning are assessed. Third, the ethical and societal dimension has no outcome measurement of any kind.

The practical consequence is that the outcomes most often invoked in public debates about technology in schools are those least supported by the evidence used to buy, deploy, and evaluate it. Policies restricting devices in schools, for example, are spreading on the basis of correlational findings (D'Addio, 2026). Conversely, AI tools are adopted on the basis of learning evidence that rarely touches well-being. Meanwhile, the ethical frameworks proliferating at every level of governance lack any way of measuring what they claim to protect.



Conclusion

This report set out to establish what is known about the socio-economic returns on investment in digital transformation and AI in education. The key finding is that the digital and AI skills this investment aims to build are clearly rewarded, especially combined with expertise in a specific field and strong human skills, but the return on the investment itself has not yet been demonstrated. The obstacle is twofold: key instruments (especially direct measurements) are missing; and the measurements that do exist are not connected by a framework linking investment to skills and skills to outcomes along the chain set out in Box 1.

The gaps identified point to what such a framework would need to do. It would measure skills directly, not through qualifications, enrolment or job advertisements. It would follow outcomes beyond employment and earnings to job quality and well-being, and distinguish private, fiscal and social returns. It would reach informal workers and the people and countries with least access to technology and training. It would keep pace with skills that lose their value quickly. And it would draw on knowledge that existing data misses: employers' understanding of the skills actually used at work, and young people's experience of how AI is shaping their choices.

Building and testing such a framework is the natural next step. Future research, including the proposed second phase of this project, would need to trace interventions from spending to the skills they are meant to build, assess digital and AI skills directly, compare outcomes against credible comparison groups and follow participants long enough to see whether gains last, including in informal settings. Building measurement in from the start, fairly and flexibly, and in partnership with the young people, employers, education providers, governments and partners who hold the missing knowledge, will be key to revealing whether investment in digital transformation and AI in education delivers and how it can be improved.

Annex A: Review methodology and scope boundaries

Scope boundaries: The report's scope is bounded in four respects. Returns are defined as socio-economic (earnings, employment, job quality, well-being and societal outcomes) rather than pedagogical; the effectiveness of educational technology in improving learning is outside scope except where learning outcomes are used as proxies for skills. The labour-market lens is that of Sustainable Development Goal 8: decent work and inclusive growth. The population of interest is young people and adult learners moving through formal and non-formal skills pathways, with technical and vocational education and training (TVET) given particular attention as the pathway explicitly designed to lead to employment. And the distributional question, whether vulnerable populations share in the returns, is treated as central rather than incidental, with gender, country income group and formal-versus-informal employment used as the principal axes of disaggregation. Geographic scope is global. Evidence from low- and middle-income countries is weighted in synthesis, and wherever findings from high-income countries are extrapolated to other contexts this is stated explicitly.

Sources: Five families of sources were searched: academic databases (ERIC, EconLit, Scopus, Web of Science, SSRN, NBER); the repositories of multilateral organisations (World Bank, ILO, WEF, CEDEFOP, UNESCO, OECD, IMF); research institutes and evaluation networks (J-PAL, IZA, ETF); international statistical databases, from which the figures in this report are drawn (UNESCO Institute for Statistics, ITU, Eurostat); and grey literature (government strategies, development-agency evaluations, and industry reports using proprietary data such as online job postings and professional-network profiles). The most recent material available at the time of writing was included, extending to sources published in 2026.

Assessment of evidence. Sources were not weighted equally. Causal designs (randomised and quasi-experimental evaluations, and meta-analyses restricted to counterfactual studies) were treated as the strongest evidence on returns. Large-scale direct assessments of skills were preferred over self-reported proficiency. Correlational and descriptive evidence, including vacancy-based wage estimates, tracer surveys and household-survey indicators, is reported throughout but identified as such, and estimates based on posted rather than realised wages are flagged in figure notes. Projections and scenario models are distinguished from observed outcomes wherever they appear. Industry data drawn from platform users rather than the labour force as a whole is reported with that limitation noted.

Synthesis approach: Each substantive section separates the evidence from the methods used to produce it, and each is accompanied by a table setting out the relevant measurement approaches, the unit of analysis, and the indicators generated (Tables 1 to 7). This structure reflects the review's role as a baseline for the Phase 2 pilot: to identify not only what is known, but which methods are candidates for empirical testing and where they fall short.

Annex B: Acronyms and abbreviations

AI	Artificial intelligence
ASAT	Adult Skills Assessment in Thailand
ASEAN	Association of Southeast Asian Nations
DigComp	European Digital Competence Framework for Citizens
DKAP	Digital Kids Asia-Pacific
DLI	Digital Literacy Index
DSI	Digital Skills Indicator
ECA	European Court of Auditors
EdTech	Education technology
EMIS	Education management information system
EU	European Union
EUR	Euro
GBP	Pound sterling
GDP	Gross domestic product
GEM Report	Global Education Monitoring Report
GenAI	Generative artificial intelligence
HBSC	Health Behaviour in School-aged Children
HIC	High-income country
ICILS	International Computer and Information Literacy Study
ICT	Information and communication technology
IDC	International Data Corporation
IEA	International Association for the Evaluation of Educational Achievement
ILO	International Labour Organization
IMF	International Monetary Fund
IPPR	Institute for Public Policy Research
IRR	Internal rate of return
ISCED	International Standard Classification of Education
ITU	International Telecommunication Union
IV	Instrumental variables
JRC	Joint Research Centre (European Commission)
LIC	Low-income country
LMIC	Low- and middle-income country
LSE	London School of Economics and Political Science
MICS	Multiple Indicator Cluster Surveys
NLP	Natural language processing
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
PIAAC	Programme for the International Assessment of Adult Competencies (OECD Survey of Adult Skills)
PISA	Programme for International Student Assessment
ROI	Return on investment
RRF	Recovery and Resilience Facility
SDG	Sustainable Development Goal

SIMCE TIC	Sistema de Medición de la Calidad de la Educación – Tecnologías de la Información y la Comunicación (Chile)
STEM	Science, technology, engineering and mathematics
TBI	Tony Blair Institute for Global Change
TVET	Technical and vocational education and training
UIS	UNESCO Institute for Statistics
UK	United Kingdom
UN	United Nations
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNICEF	United Nations Children's Fund
US	United States
US$	United States dollar
VET	Vocational education and training
WEF	World Economic Forum
WHO	World Health Organization

Annex C: Glossary

Term	Definition
AI literacy, skills and competences	(1) The skills, knowledge and understanding that allow providers, deployers and affected persons to make an informed deployment of AI systems, and to gain awareness of the opportunities and risks of AI and the harm it can cause (European Union, 2025). (2) The skills required to develop and maintain AI, i.e. the technical competencies of AI specialists, as distinct from the skills needed merely to use AI at work (OECD, 2026f). (3) A set of knowledge, skills and attitudes enabling learners to grasp how AI systems function, critically assess what they produce, and apply them in ethical and creative ways, organized into four domains (engaging with, creating with, managing and designing AI) comprising 19 competences (OECD and European Union, 2026).
AI skills	A continuum spanning AI literacy, applied AI skills (using AI effectively within a field of expertise) and specialist AI skills (building and maintaining AI systems). *Working definition used in this report; see the executive summary.*
Aid to education	External funding for education in low- and middle-income countries, provided by donors, international organizations and development banks (UNESCO, 2026d).
Algorithmic management	The use of software and AI to allocate tasks, set the pace of work, monitor workers or evaluate their performance (De Cuyper et al., 2025).
Digital skills and competences	(1) A range of abilities to use digital devices, communication applications and networks to access and manage information, enabling people to create and share digital content, communicate and collaborate, and solve problems for effective and creative self-fulfilment in life, learning, work and social activities (UNESCO, 2018; 2023a). (2) The ability to use ICTs in ways that help individuals achieve beneficial, high-quality outcomes for themselves and others, and reduce potential harm from more negative aspects of digital engagement (ITU, 2018; UNESCO, 2023a). (3) The confident, critical and responsible use of digital technologies for learning, work and participation in society, including information and data literacy, communication and collaboration, media literacy, digital content creation (including programming), safety, intellectual property, problem-solving and critical thinking (European Commission, 2018; UNESCO, 2023a).
Digital transformation	The redesign of the education ecosystem, including its operational, organizational and cultural aspects, by integrating digital technology and data and managing the changes they bring. It requires the system to evaluate, re-engineer and reimagine its functions and outcomes, for example by ensuring that decision-making at all levels is digitally enabled and informed by data. It has no well-defined endpoint and involves continuous improvement (Reinitz, 2020; Rajasekaran et al., 2024).
Digitalisation	Converting analogue processes into digital ones, such as automating existing processes, retraining workers to use computers, or managing education data in an education management information system (EMIS). It goes further than digitisation but does not yet use digital technology to bring about systemic or organizational change (Reinitz, 2020; Rajasekaran et al., 2024).
Digitisation	Converting physical objects into a digital format, for example scanning paper-based education records into PDF files stored on a computer, so that data can be processed, stored and transmitted digitally (Reinitz, 2020; Rajasekaran et al., 2024).

Term	Definition
Education technology (EdTech)	The use of digital technologies, software and tools to support teaching, learning, assessment and educational management (UNESCO, 2023a).
Exposure to AI	The extent to which the tasks in a job could be performed or changed by AI. Exposure measures potential impact, not actual job loss (Cazzaniga et al., 2024; Gmyrek et al., 2025).
Fiscal returns	The return to governments from education: additional tax revenue and reduced transfer payments generated by an educated person, relative to public spending on their education (OECD, 2021).
Generative AI (GenAI)	AI technology that automatically generates content, such as text, images, audio or code, in response to prompts written in everyday language (UNESCO, 2023b).
GenAI literacy	The ability to use generative AI tools effectively for a task, to understand how they produce their outputs, and to judge the accuracy, reliability and limitations of what they generate; one component of AI literacy. *Working definition used in this report, drawing on OECD and European Union (2026) and Jin et al. (2025).*
GenAI skills	The skills needed to work with generative AI, ranging from GenAI literacy to the specialist skills needed to develop and adapt generative AI systems. *Working definition used in this report, drawing on Martins-Neto et al. (2026).*
Human capital	The stock of knowledge, skills, competencies and attributes embodied in people that enable them to be productive (Schultz, 1961; Becker, 1975).
Informal employment	Work that is not covered, in law or in practice, by labour legislation, social protection or employment benefits (ILO, 2024).
Information and communication technology (ICT)	Technologies that enable the creation, storage, processing, transmission and exchange of information through electronic means, including computers, networks and telecommunications (ITU, 2022).
ICT education	Education whose field of study is information and communication technologies, as classified in the International Standard Classification of Education (ISCED-F 2013, field 06); used in this report to refer to employed people whose highest qualification is in ICT (Eurostat, 2026c).
ICT skills	The skills to use information and communication technologies, measured for SDG indicator 4.4.1 by whether people report having carried out specific computer-related activities, such as copying files, sending emails with attachments, using spreadsheet formulas or writing a computer program (ITU, 2018).
ICT specialists	Workers who can develop, operate and maintain ICT systems, and for whom ICT is the main part of their job (Eurostat, 2026b).
Internal rate of return to education	The discount rate that equates the present value of the costs of education (tuition and foregone earnings) with the present value of its benefits (higher lifetime earnings) (Heckman et al., 2006).
Overqualification	Having a higher level of education than one's job requires (ILO and OECD, 2025).
Private returns	The benefits of education to individuals, mainly higher earnings and better employment (Psacharopoulos and Patrinos, 2018).
Return to skills	The earnings gain associated with directly measured cognitive skills, such as literacy, numeracy and problem-solving, as opposed to years or levels of schooling (Hanushek et al., 2015; Hanushek and Woessmann, 2008).
Returns to education	The gain in earnings (or welfare) attributable to an additional unit of education, usually a year or a qualification level, expressed as a percentage, analogous to the return on a financial investment (Psacharopoulos and Patrinos, 2018).

Term	Definition
Social returns	The benefits of education to society as a whole, such as lower crime, greater civic participation and benefits that carry over to the next generation (Psacharopoulos and Patrinos, 2018).
Technical and vocational education and training (TVET)	Education, training and skills development relating to a wide range of occupations and areas of work, including work-based learning and continuing training, which can lead to qualifications (UNESCO, 2015).
Total factor productivity	A measure of how efficiently an economy combines labour and capital to produce output, capturing growth not explained by increases in those inputs (OECD, 2001).

Annex D: Calculating AI's impact on jobs: different methods, different answers

Estimates of how AI will affect employment have changed substantially as methods have developed, and much of the variation between them reflects the method used, not differences in the underlying data. Three generations of studies can be distinguished, alongside a growing use of scenario models.

Occupation-based estimates: The first studies treated entire occupations as the unit of analysis, using expert classification to categorize jobs as either automatable or not. Early estimates suggested that up to 47% of US employment was at high risk of computerization (Frey and Osborne, 2017). This approach is now largely discredited, as it assumed that if one task could be automated, the entire job was automatable. Replicating the analysis at the task level reduced the exposure estimate to 9% (Arntz et al., 2016), a fivefold difference that reflects a methodological difference rather than a reliable finding.

Exposure indices: A second generation shifted towards composite exposure indices that combined ability-based mappings, machine-learning suitability rubrics, and text-based matching of patents to job descriptions (Brynjolfsson et al., 2018; Felten et al., 2018; Webb, 2020). These indices measured the technological overlap between AI capabilities and job tasks rather than economic impact. Studies incorporating all three methods found measurable exposure across the economy, concentrated in high-skill work, but no aggregate effects on employment or wages (Acemoglu et al., 2020). The only firmly causal evidence from this period related to industrial robots rather than cognitive AI (Acemoglu and Restrepo, 2020).

Studies of large language models and actual deployment: **the most recent studies have disproved an earlier assumption: creative, cognitive and high-skill roles, previously considered insulated, are now among the most exposed** (Eloundou et al., 2023). The latest methods have incorporated tools that use natural language processing (NLP) to classify tasks by how readily AI could perform them (Xu et al., 2025; Hampole et al., 2025), and quasi-experimental designs have shifted towards causal estimates based on actual deployment. For example, GenAI increased productivity by 14–15% in a large firm, with the least experienced workers benefiting the most (Brynjolfsson et al., 2025). Job postings fell by 17% for automation-prone roles while rising by 22% for augmentation-prone ones (Chen et al., 2024).

Scenario models: scenario-based modelling has become a popular tool, even as its outcomes vary widely: when applied to the same UK task data, different adoption scenarios predict outcomes ranging from zero job losses with a 13% GDP gain to eight million jobs lost with no GDP gain (TBI, 2024; IPPR, 2024).

Annex E: Tables

Table 1. How returns to education are measured

Measurement approach	Methodology	Unit/output measured	Specific indicators
Mincerian earnings-function approach	Mincerian wage regressions – Ordinary Least Squares (OLS), Instrumental Variables (IV), and twin studies; a cognitive-skills variant substitutes test scores for years of schooling	Earnings	Wage premium per year of schooling; wage premium per standard deviation of cognitive skill
Discount / internal-rate-of-return method	Cost-benefit analysis applied to the schooling decision: the discount rate that equalises the stream of benefits and costs of an additional year of schooling	Earnings, net of direct and opportunity costs	Internal rate of return (IRR) to a year/level of schooling
Corporate / workforce training return-on-investment (ROI)	Training ROI calculation	Productivity / monetised output	Monetised productivity gain per training dollar spent

Source: Author's elaboration, drawing on Psacharopoulos and Patrinos, 2018; Patrinos, 2024 and Heckman et al., 2006 for the Mincerian and internal-rate-of-return approaches; Hanushek and Woessmann, 2008 and Hanushek et al., 2015 for the cognitive-skills variant; and Schueler et al., 2017 for training return-on-investment frameworks.

Table 2. How returns to digital skills are measured: three lenses on labour-market demand

Measurement approach	Methodology	Unit/output measured	Specific indicators
Assessment-based returns to digital proficiency	Wage regressions linking directly assessed ICT proficiency to earnings controlled for education and observables (e.g., PIAAC-based analyses)	Worker; realized earnings	Wage premium per standard deviation of ICT proficiency; premium relative to numeracy; returns in digitally intensive occupations
Skill-bundle analysis of job postings	Text analysis of skills listed in vacancies, related to posted wages and firm outcomes, within and across occupations	Vacancy; posted skill requirements	Share of wage variation explained by skill demand; wage premium per additional listed skill
Vacancy-based estimation of digital and AI skill premiums	Large-scale matching of digital and AI skill requirements in postings to posted wages, disaggregated by skill level and occupation type	Vacancy; posted wages	Wage premium per additional digital skill; premium by skill level; premium for AI and GenAI skills

Source: Author's elaboration, drawing on Hanushek et al., 2015, Grundke et al., 2018, Falck et al., 2021 and Langer and Wiederhold, 2023 for assessment-based returns; Deming and Kahn, 2018 and Ziegler, 2024 for skill-bundle analysis of job postings; and Garcia-Lazaro et al., 2025, Lightcast, 2025 and Martins-Neto et al., 2026 for vacancy-based estimation of digital and AI skill premiums.

Table 3. Approaches to evaluating the economic returns to TVET

Measurement Approach	Methodology	Unit/output Measured	Specific Indicators
Mincerian wage regressions with a VET indicator	Wage regressions estimating the differential associated with vocational qualifications, controlling for observables	Earnings	Wage premium for VET holders relative to general education or no training
Matching and selection-correction methods	Propensity score matching, inverse-probability-weighted regression adjustment, Heckman correction – constructing counterfactuals from observably similar non-participants	Earnings; employment status	Average treatment effect on the treated (wage premium; employment probability differential)
Randomised and quasi-experimental designs	Random assignment to training programmes or exploitation of natural experiments (e.g., voucher lotteries)	Employment; earnings	Causal effect on employment probability and earnings relative to control group
Meta-analysis with causal-inference filters	Synthesis of effect sizes across studies restricted to counterfactual designs	Pooled labour market outcomes	Standardised effect sizes (e.g., Hedges' g) on employment and wages
Graduate tracer surveys	Follow-up surveys of TVET graduates after programme completion; the sector's own standard instrument	Employment destination	Placement rates; time to employment; job-training match (descriptive, not attributable impact)

Source: Author's elaboration, drawing on Hanushek et al., 2017, Hampf and Woessmann, 2016 and UNDP, 2019 for Mincerian regressions with a VET indicator; The World Bank, UNESCO and ILO, 2023 for matching and selection-correction methods; Barrera-Osorio et al., 2020 and World Bank and ILO, 2024 for randomised and quasi-experimental designs; Kemper et al., 2026 and World Bank and ILO, 2024 for meta-analysis with causal-inference filters; and Jones et al., 2021 and Schueler et al., 2017 for graduate tracer surveys.

Table 4. The policy landscape for digital and AI integration in TVET is expanding at every level of governance

Governance level	Who acts	Strategic approach	Initiatives
Regional and international frameworks	Regional bodies (for example, African Union, ASEAN, EU) setting direction and harmonising national efforts	Continental and regional ecosystems, shared competency frameworks	• Pan-African Initiative for the Digital Transformation of TVET • ASEAN Year of Skills 2025 and TVET Council Work Plan 2021–2030 • EU Digital Education Action Plan

Governance level	Who acts	Strategic approach	Initiatives
National strategies	Governments translating regional ambition into policy, funding, and institutional structures	Divergent by income level: comprehensive whole-of-government alignment in high-income countries; targeted, cost-conscious models in middle-income countries	• Australia's cross-ministerial AI strategy and AI technical standard for government • Malaysia's Digital Economy Blueprint and AI-powered National TVET Placement Platform • Viet Nam's low-cost "multiplier model" of peer-based instructor training
Institutional practices	TVET institutions and industry partners piloting tools in classrooms and workshops	Experimentation with immersive simulation, AI tutors, content-integrated AI, and whole-institution transformation	• AI just-in-time learning assistant at Costa Rica's National Apprenticeship Institute • Whole-institution digital transformation at Shenzhen Polytechnic University (China)

Source: UNESCO, 2026c.

Table 5. The OECD Survey of Adult Skills (PIAAC, Cycle 2): What it measures and how

Component	Measurement method	Details
Survey design	Nationally representative household survey of adults aged 16-65	Approx.160,000 adults across 31 countries and economies, representing 673 million people; internationally standardised technical protocols; response rates of 27-73%, with non-response bias analyses conducted and data quality independently certified
Skills (literacy, numeracy, adaptive problem solving)	Direct assessment: tablet-based, adaptive testing	Fully-digital delivery in Cycle 2 (Cycle 1 offered a paper option); items designed to reflect real-world, digitally-mediated information processing; a "doorstep interview" in more than 40 languages reduces coverage bias among low-language-proficiency adults

Component	Measurement method	Details
Labour market outcomes (wages, employment, participation)	Self-reported via background questionnaire	Earnings include bonuses and self-employment income; associations with skills estimated through regressions adjusted for socio-demographic characteristics, with skills and years of education entered independently
Social outcomes (life satisfaction, self-reported health, political efficacy, social trust, volunteering)	Self-reported via background questionnaire: 0-10 scales (aligned with the European Social Survey) and Likert-type items	Positive outcomes defined by threshold (e.g., 7 or above on 0-10 scales; "very good/excellent" for health; any volunteering in the past year)

Source: OECD, 2024a.

Table 6. Selected international and national digital skills assessments

Assessment	Type	Purpose	What it measures
International assessments			
SDG indicator 4.4.1: Proportion of youth and adults with ICT skills – ITU	Statistical monitoring indicator; self-reported household survey data	Global monitoring of SDG target 4.4 on youth/adult ICT skills	Self-reported performance of nine computer-related activities
Multiple indicator Cluster Surveys (MICS) – UNICEF	Household survey; self-reported	Household data on children, women and men; a key source for SDG 4.4.1 in low- and middle-income countries	Self-reported performance of nine computer-related activities
Digital Skills Indicator (DSI) – European Union	Composite statistical indicator built from Eurostat's survey on ICT usage in households and by individuals; self-reported	Track EU policy targets (Digital Decade goal: 80% of adults with at least basic digital skills by 2030)	Self-reported activities mapped to DigComp competence areas, aggregated into "basic" / "above basic" skill levels
International Computer and Information Literacy Study (ICILS) – IEA	Summative, large-scale; task-based	Only international large-scale assessment devoted solely to digital literacy; cross-country comparison and trend monitoring for grade-8 students	Computer and information literacy (plus optional computational thinking) through authentic, task-based computer modules
Programme for International Student Assessment (PISA) – OECD	Summative, large-scale; core test plus self-reported questionnaires	Compare learning outcomes of 15-year-olds across countries	Core domains delivered digitally; digital skills enter mainly via self-reported ICT familiarity questionnaires and periodic modules

Assessment	Type	Purpose	What it measures
Programme for the International Assessment of Adult Competencies (PIAAC) – OECD	Summative, large-scale; task-based	Cross-country assessment of adult (16-65) skills	Task-based problem solving in technology-rich environments, alongside literacy and numeracy
Digital Kids Asia-Pacific (DKAP) Survey – UNESCO Bangkok	Regional school-based survey; self-reported	Assess digital citizenship of 15-year-old students; piloted in Indonesia, Lao PDR, the Philippines and Thailand	Self-reported ICT literacy, attitudes and behaviours
National-level examples			
Adult Skills Assessment in Thailand (ASAT) – The World Bank	Summative, large-scale; task-based	First nationally and regionally representative measure of adults' (15-64) foundational skills	Task-based digital skills – operating digital devices/ software and information and data literacy – on an original Level 0-2 proficiency scale, plus literacy and socioemotional skills
Digital Literacy Index (DLI) – Bangladesh	Household survey; self-reported plus hands-on tests	First nationwide survey of digital literacy in rural Bangladesh (6,500 households), assessing citizens' capacity to use digitized public services	Access to devices/connectivity and basic skills, including practical tests of internet browsing and visual icon identification
Pix – France	Formative; task-based, adaptive	Assessment and certification of digital competences for students, teachers, and workers	Adaptive online test aligned to DigComp 2.2 (difficulty adjusts to the respondent's level)
Sistema de Medición de la Calidad de la Educación (SIMCE TIC) – Chile	Formative; task-based	National measurement of secondary students' ICT skills	Task-based performance in a simulated digital environment, against Chile's own SIMCE TIC framework
IKANOS – Spain (Basque Region)	Formative; task-based	Self-diagnosis so citizens, students, and workers can plan their own skills development	Test aligned to DigComp 2.2 and DigCompEdu

Source: Author's analysis.

Table 7. How well-being, ethical, and societal outcomes are measured: main instruments

Instrument	Coverage and design	What it measures on well-being, technology, and AI	Approach
PISA well-being module – OECD	15-year-olds, 80+ systems, alongside the cognitive assessment	Life satisfaction, belonging, anxiety; digital device use and its correlates with well-being and performance	Self-report questionnaire, linked to assessment data
Survey on Social and Emotional Skills – OECD	10- and 15-year-olds; growing set of cities and countries	Social-emotional skills (e.g. emotional regulation, collaboration); associations with digital engagement	Self-report scales (students, parents, teachers)
Health Behaviour in school-aged Children (HBSC) – WHO	11-, 13-, 15-year-olds; 40+ countries; four-year cycles	Adolescent health and well-being; problematic social media and gaming use	Self-report school survey
EU Kids Online / Global Kids Online -LSE/UNICEF	Children 9-17; multi-country	Online risks, harms, and opportunities as reported by children themselves	Self-report survey
European Working Conditions Survey – Eurofound	Workers, EU-wide	Working conditions and well-being; newer rounds cover digital monitoring and algorithmic management	Self-report survey
JRC AIMWORK survey – European Commission	Workers; all EU Member States; 2024-2025 (successor to the AMPWork pilot)	Use of digital tools and AI at work; prevalence and forms of digital monitoring (working time, physical, activity) and algorithmic management (automated work allocation, pace-setting, automated evaluation); platformisation and its association with working conditions	Self-report survey
OECD AI worker and employer surveys	Workers and firms in selected sectors and countries	Reported effects of AI adoption on job quality, stress, and satisfaction	Self-report survey
UNESCO readiness assessment – AI ethics recommendation	Governments; global	Whether governance arrangements for ethical AI are in place – an input, not an outcome, measure	Government self-assessment against a framework
OECD AI Incidents Monitor	Global; continuous	Documented AI-related incidents and harms, including in education	Incident tracking from public reports

Source: Author's elaboration, drawing on the technical documentation of each instrument: OECD, 2023a; 2024b; 2023d, WHO, 2024a; 2024b, Smahel et al., 2020, Eurofound, 2022, De Cuyper et al., 2025, Gonzalez Vazquez et al., 2025 and UNESCO, 2021.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2020). *AI and jobs: Evidence from online vacancies* (NBER Working Paper No. 28257). National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w28257/w28257.pdf

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy, 128*(6), 2188-2244. https://www.journals.uchicago.edu/doi/10.1086/705716

African Union. (2020). *The digital transformation strategy for Africa (2020-2030)*. African Union. https://au.int/en/documents/20200518/digital-transformation-strategy-africa-2020-2030

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis* (OECD Social, Employment and Migration Working Papers No. 189). OECD Publishing. https://www.oecd.org/en/publications/the-risk-of-automation-for-jobs-in-oecd-countries_5jlz9h56dvq7-en.html

Barrera-Osorio, F., Kugler, A., & Silliman, M. (2020). *Hard and soft skills in vocational training: Experimental evidence from Colombia* (NBER Working Paper No. 27548). National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w27548/w27548.pdf

Becker, G. S. (1975). *Human capital: A theoretical and empirical analysis, with special reference to education* (2nd ed.). National Bureau of Economic Research. https://www.nber.org/system/files/chapters/c3730/c3730.pdf

Bick, A., Blandin, A., & Deming, D. J. (2024). *The rapid adoption of generative AI* (NBER Working Paper No. 32966). National Bureau of Economic Research. https://doi.org/10.3386/w32966

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics, 140*(2), 889-942. https://academic.oup.com/qje/article/140/2/889/7990658

Brynjolfsson, E., Mitchell, T., & Rock, D. (2018). What can machines learn and what does it mean for occupations and the economy? *AEA Papers and Proceedings, 108*, 43-47. https://www.aeaweb.org/articles?id=10.1257/pandp.20181019

Bulman, G., & Fairlie, R. W. (2016). Technology and education: Computers, software, and the internet. In *Handbook of the Economics of Education* (Vol. 5, pp. 239-280). Elsevier. https://www.sciencedirect.com/science/chapter/handbook/abs/pii/B9780444634597000051

Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., Rockall, E., & Tavares, M. M. (2024). *Gen-AI: Artificial intelligence and the future of work* (IMF Staff Discussion Note SDN/2024/001). International Monetary Fund. https://www.imf.org/-/media/files/publications/sdn/2024/english/sdnea2024001.pdf

Chen, Z., et al. (2024). *Displacement or complementarity? The labor market impact of generative AI* (Harvard Business School Working Paper No. 25-039). https://www.hbs.edu/ris/Publication%20Files/25-039_05fbec84-1f23-459b-8410-e3cd7ab6c88a.pdf

Comin, D., & Hobijn, B. (2010). An exploration of technology diffusion. *American Economic Review*, 100(5), 2031-2059. https://www.aeaweb.org/articles?id=10.1257/aer.100.5.2031

Craig, R. and Stewart, G. (2025). *Essential Skills Tracker 2025: Driving social mobility and growth through the AI transition*. London: Skills Builder Partnership and Edge Foundation. https://www.skillsbuilder.org/global/file/essential-skills-tracker-2025

D'Addio, A. C. (2026, March 19). *Phone bans in schools are spreading worldwide as the policy debate rages on*. World Education Blog. https://world-education-blog.org/2026/03/19/phone-bans-in-schools-are-spreading-worldwide-as-the-policy-debate-rages-on/

De Cuyper, P., et al. (2025). Methodology of the AIM-WORK survey (JRC Survey on Artificial Intelligence and Algorithmic Management in the Workplace) - JRC Working Papers Series on Labour, Education and Technology 2025/06, European Commission, Seville, 2025, JRC143933. https://publications.jrc.ec.europa.eu/repository/handle/JRC143933

Dee, T. S. (2004). Are there civic returns to education? *Journal of Public Economics, 88*(9-10), 1697-1720. https://tom-dee.github.io/files/jpubec04.pdf

Deming, D. J., & Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics, 36*(S1), S337-S369. https://www.journals.uchicago.edu/doi/10.1086/694106

Deming, D. J., & Noray, K. (2020). *Earnings Dynamics, changing job skills, and STEM careers* https://static1.squarespace.com/static/60832ecef615231cedd30911/t/60871f691664f41cb424b379/1619468137800/DemingNoray_STEM.pdf

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2023). *GPTs are GPTs: An early look at the labor market impact potential of large language models*. arXiv. https://arxiv.org/abs/2303.10130

Eurofound. (2022). *Working conditions in the time of COVID-19: Implications for the future* (EWCTS 2021 series). https://www.eurofound.europa.eu/en/publications/all/working-conditions-time-covid-19-implications-future

European Commission. (2018). *Council Recommendation of 22 May 2018 on key competences for lifelong learning*. Official Journal of the European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32018H0604(01)&rid=7

European Commission. (2026). *Digital measures under the Recovery and Resilience Facility: Economic impacts at macro, sectoral and country level*. Publications Office of the European Union. https://economy-finance.ec.europa.eu/publications/digital-measures-under-recovery-and-resilience-facility-economic-impacts-macro-sectoral-and-country_en

European Court of Auditors. (2025). *Support from the Recovery and Resilience Facility for the digital transition in EU member states: A missed opportunity to focus on strategy to meet digital needs* (Special Report 13/2025). European Court of Auditors. https://www.eca.europa.eu/en/publications/sr-2025-13

European Union. (2021). *National recovery and resilience plans: Digital skills and jobs*. https://digital-skills-jobs.europa.eu/en/actions/national-initiatives/national-recovery-plans

European Union. (2022). *Decision (EU) 2022/2481 establishing the Digital Decade Policy Programme 2030*. Official Journal of the European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32022D2481

European Union. (2025). *Article 4: AI literacy – EU Artificial Intelligence Act*. https://artificialintelligenceact.eu/article/4/

Eurostat. (2026a). *Individuals' level of digital skills* [Data set, sdg_04_70]. https://ec.europa.eu/eurostat/databrowser/view/sdg_04_70/default/table?lang=en

Eurostat. (2026b). *Employed ICT specialists by age* [Data set, isoc_sks_itspa]. https://ec.europa.eu/eurostat/databrowser/view/isoc_sks_itspa/default/table?lang=en

Eurostat. (2026c). *Employed persons with ICT education by age* [Data set, isoc_ski_itage]. https://ec.europa.eu/eurostat/databrowser/view/isoc_ski_itage/default/table?lang=en

Falck, O., Heimisch-Roecker, A., & Wiederhold, S. (2021). Returns to ICT skills. *Research Policy, 50*(7), 104064. https://www.sciencedirect.com/science/article/abs/pii/S0048733320301426

Felten, E. W., Raj, M., & Seamans, R. (2018). A method to link advances in AI to occupational abilities. *AEA Papers and Proceedings, 108*, 54–57. https://doi.org/10.1257/pandp.20181021

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280. https://www.sciencedirect.com/science/article/abs/pii/S0040162516302244

Gallup and Lumina Foundation (2026). *State of Higher Education 2026*. https://www.gallup.com/analytics/644939/state-of-higher-education.aspx

Garcia-Lazaro, A., Mendez-Astudillo, J., Lattanzio, S., Larkin, C., & Newnes, L. (2025). The digital skill premium: Evidence from job vacancy data. *Economics Letters, 250*, 112294. https://www.sciencedirect.com/science/article/pii/S0165176525001314

Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., Rosłaniec, K., & Troszyński, M. (2025). *Generative AI and jobs: A refined global index of occupational exposure* (ILO Working Paper 140). International Labour Organization. https://www.ilo.org/publications/generative-ai-and-jobs-refined-global-index-occupational-exposure

Gonzalez Vazquez, I., et al. (2025). Digital Monitoring, Algorithmic Management and the Platformisation of Work in Europe, Publications Office of the European Union, Luxembourg, 2025, JRC143072. https://publications.jrc.ec.europa.eu/repository/handle/JRC143072

Government of India. (2026). *Digital India: 11 years of transformation* [Press release]. Press Information Bureau. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2278422&reg=48&lang=1

Grundke, R., Marcolin, L., Nguyen, T. L. B., & Squicciarini, M. (2018). *Which skills for the digital era? Returns to skills analysis* (OECD Science, Technology and Industry Working Papers No. 2018/09). OECD Publishing. https://www.oecd.org/en/publications/which-skills-for-the-digital-era_9a9479b5-en.html

Hampf, F., & Woessmann, L. (2016). *Vocational vs. general education and employment over the life-cycle: New evidence from PIAAC* (IZA Discussion Paper No. 10298). https://docs.iza.org/dp10298.pdf

Hampole, M., Papanikolaou, D., Schmidt, L. D. W., & Seegmiller, B. (2025). *Artificial intelligence and the labor market* (NBER Working Paper No. 33509). https://www.nber.org/system/files/working_papers/w33509/w33509.pdf

Hanushek, E. A., Schwerdt, G., Wiederhold, S., & Woessmann, L. (2015). Returns to skills around the world: Evidence from PIAAC. *European Economic Review, 73*, 103-130. https://hanushek.stanford.edu/sites/default/files/publications/Hanushek%2BSchwerdt%2BWiederhold%2BWoessmann%202015%20EER%2073.pdf

Hanushek, E. A., Schwerdt, G., Woessmann, L., & Zhang, L. (2017). General education, vocational education, and labor-market outcomes over the lifecycle. *Journal of Human Resources, 52*(1), 48-87. https://hanushek.stanford.edu/sites/default/files/publications/Hanushek%2BSchwerdt%2BWoessmann%2BZhang%202017%20JHR%2052%281%29_0.pdf

Hanushek, E. A., & Woessmann, L. (2008). The role of cognitive skills in economic development. *Journal of Economic Literature, 46*(3), 607-668. https://gwern.net/doc/iq/ses/2008-hanushek.pdf

Heckman, J. J., Lochner, L. J., & Todd, P. E. (2006). Earnings functions, rates of return and treatment effects: The Mincer equation and beyond. In *Handbook of the Economics of Education* (Vol. 1, pp. 307-458). Elsevier. https://jenni.uchicago.edu/papers/Heckman_Lochner_etal_2006_HEE_v1_ch7.pdf

Hornberger, M., Bewersdorff, A., & Nerdel, C. (2025). A multinational assessment of AI literacy among university students in Germany, the UK, and the US. *Computers in Human Behavior: Artificial Human*. https://www.sciencedirect.com/science/article/pii/S2949882125000167

IDC. (2025). *IDC predicts AI solutions & services will generate global impact of $22.3 trillion by 2030* [Press release]. IDC. https://www.idc.com/resource-center/press-releases/idc-predicts-ai-solutions-services-will-generate-global-impact-of-22-3-trillion-by-2030/

International Labour Organization. (2024). *Global employment trends for youth 2024*. ILO. https://www.ilo.org/sites/default/files/2024-09/GET_2024_EN%20web.pdf

International Labour Organization & OECD. (2025). *Youth employment* (Priority 1 paper). ILO & OECD. https://www.ilo.org/sites/default/files/2025-02/Priority%201%20-%20Youth%20Employment%20Paper_ILO_OECD_revised.pdf

International Labour Organization. (2026). *Global employment trends for youth 2026*. ILO. https://www.ilo.org/sites/default/files/2026-09/9789220437612_PDFA_Web_ENG.pdf

International Monetary Fund. (2025). *World economic outlook: Global economy in flux, prospects remain dim, October 2025*. International Monetary Fund. https://www.imf.org/en/publications/weo/issues/2025/10/14/world-economic-outlook-october-2025

International Telecommunication Union. (2018). *Measuring the information society report 2018* (Vol. 1). ITU. https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2018/MISR-2018-Vol-1-E.pdf

International Telecommunication Union. (2022). *Measuring digital development: Facts and figures 2022*. ITU. https://www.itu.int/hub/publication/d-ind-ict_mdd-2022/

International Telecommunication Union. (2025). *Econometric modelling of broadband and digitisation impacts on GDP*. ITU. https://www.itu.int/dms_pub/itu-d/opb/pref/D-PREF-ECON.MOD-2025-PDF-E.pdf

IPPR. (2024). *Transformed by AI: How generative artificial intelligence could affect work in the UK*. Institute for Public Policy Research. https://www.ippr.org/articles/transformed-by-ai

Jiang, X. (2021). Women in STEM: Ability, preference, and value. *Labour Economics, 70*, 101991. https://www.sciencedirect.com/science/article/abs/pii/S0927537121000269

Jin, Y., et al. (2025). Generative AI Literacy Assessment Test (GLAT). *Computers and Education: Artificial Intelligence*. https://www.sciencedirect.com/science/article/pii/S2666920X25000761

Jones, S., et al. (2021). *A survey of school-to-work transition of technical and vocational training graduates in Mozambique*. UNU-WIDER. https://www.wider.unu.edu/publication/survey-school-work-transition-technical-and-vocational-training-graduates-mozambique

Kemper, J., Au Yong Lyn, A., McDonald, P., & Renold, U. (2026). Labor market outcomes of formal vocational education and training: A meta-analysis. *Education Economics, 34*(2), 267-291. https://www.tandfonline.com/doi/full/10.1080/09645292.2025.2579799

Langer, C., & Wiederhold, S. (2023). *The value of early-career skills*. Harvard Growth Lab. https://growthlab.hks.harvard.edu/publication/the-value-of-early-career-skills/

Le, K., & Nguyen, M. (2021). Education and political engagement. *International Journal of Educational Development, 85*, 102441. https://econpapers.repec.org/article/eeeinjoed/v_3a85_3ay_3a2021_3ai_3ac_3as0738059321000948.htm

Li, C., Tsuei, S. H. T., & Wu, H. (2026). AI literacy among Chinese medical students: Cross-sectional examination of individual and environmental factors. *JMIR Medical Education*, 12, e80604. https://mededu.jmir.org/2026/1/e80604

Lightcast. (2025). *Beyond the buzz: Developing the AI skills employers actually need*. https://lightcast.io/resources/research/beyond-the-buzz-developing-the-ai-skills-employers-actually-need

LinkedIn Economic Graph Research Institute. (2026). *The triple penalty*. LinkedIn.

Liu, Y., & Wang, H. (2024). *Who on earth is using generative AI?* (Policy Research Working Paper No. 10870). World Bank. http://hdl.handle.net/10986/42071

Liu, Y., Huang, J., & Wang, H. (2025). *Who on earth is using generative AI? Global trends and shifts in 2025*. World Bank. https://documents1.worldbank.org/curated/en/099856110152535288/pdf/IDU-42736e6b-48fb-45e6-8638-cec68a650f40.pdf

Lochner, L., & Moretti, E. (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *American Economic Review, 94*(1), 155-189. https://www.jstor.org/stable/3592774

Machin, S., & Sandi, M. (2025). Crime and Education. *Annual Review of Economics*, 17, 241–260. https://doi.org/10.1146/annurev-economics-090324-035606

Martins-Neto, A., et al. (2026). *Click, code, earn: The returns to digital skills*. World Bank. https://documents1.worldbank.org/curated/en/099451102172652767/pdf/IDU-e779b9af-e9b1-43ae-a2c5-9679dbf2d829.pdf

Maslej, N., Fattorini, L., Perrault, R., et al. (2025). *The AI Index 2025 annual report*. Stanford Institute for Human-Centered AI. https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf

Michelmore, K., & Sassler, S. (2016). Explaining the gender wage gap in STEM: Does field sex composition matter? *RSF: The Russell Sage Foundation Journal of the Social Sciences, 2*(4), 194-215. https://www.rsfjournal.org/content/2/4/194

Montenegro, C. E., & Patrinos, H. A. (2023). A data set of comparable estimates of the private rate of return to schooling. *International Journal of Manpower, 44*(6), 1248-1268. https://www.emerald.com/ijm/article-abstract/44/6/1248/141046

OECD. (2001). *Measuring productivity: Measurement of aggregate and industry-level productivity growth (OECD manual)*. OECD Publishing. https://doi.org/10.1787/9789264194519-en

OECD. (2020). *Education at a Glance*. OECD Publishing. https://doi.org/10.1787/69096873-en

OECD. (2021). *Education at a glance 2021: OECD indicators*. OECD Publishing. https://www.oecd.org/en/topics/public-returns-from-education.html

OECD. (2023a). *PISA 2022 results (Volume I): The state of learning and equity in education*. OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/12/pisa-2022-results-volume-i_76772a36/53f23881-en.pdf

OECD. (2023d). *The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers*. OECD Publishing. https://www.oecd.org/en/publications/2023/03/the-impact-of-ai-on-the-workplace-main-findings-from-the-oecd-ai-surveys-of-employers-and-workers_ad686e91.html

OECD. (2023e). *OECD digital education outlook 2023*. OECD Publishing. https://www.oecd.org/en/publications/2023/12/oecd-digital-education-outlook-2023_c827b81a.html

OECD. (2024a). *Do adults have the skills they need to thrive in a changing world? Survey of Adult Skills 2023*. OECD Publishing. https://www.oecd.org/en/publications/2024/12/do-adults-have-the-skills-they-need-to-thrive-in-a-changing-world_4396f1f1.html

OECD. (2024b). *Social and emotional skills for better lives: Findings from the OECD Survey on Social and Emotional Skills 2023*. OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/04/social-and-emotional-skills-for-better-lives_7af2f463/35ca7b7c-en.pdf

OECD. (2024c). *Artificial intelligence and the changing demand for skills in the labour market* (OECD Artificial Intelligence Papers). OECD Publishing. https://www.oecd.org/en/publications/artificial-intelligence-and-the-changing-demand-for-skills-in-the-labour-market_88684e36-en.html

OECD. (2025). *Education at a glance 2025: OECD indicators*. OECD Publishing. https://www.oecd.org/en/publications/2025/09/education-at-a-glance-2025_c58fc9ae.html

OECD. (2026a). *A skills-first labour market*. OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2026/06/a-skills-first-labour-market_bd036db7/2e1b85f0-en.pdf

OECD. (2026b). *Developing vocational education and training with artificial intelligence*. OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2026/06/developing-vocational-education-and-training-with-artificial-intelligence_b7efe1ae/e9f76b4e-en.pdf

OECD. (2026c). *OECD employment outlook 2026*. OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2026/07/oecd-employment-outlook-2026_a41e8b9f/7e710f54-en.pdf

OECD. (2026d). *OECD digital education outlook 2026*. OECD Publishing. https://www.oecd.org/en/publications/oecd-digital-education-outlook-2026_062a7394-en.html

OECD. (2026e). *PISA 2029: Media and artificial intelligence literacy*. https://www.oecd.org/en/about/projects/pisa-2029-media-and-artificial-intelligence-literacy.html

OECD. (2026f). *AI and skills: What we know so far* (OECD Policy Brief). OECD Publishing. https://www.oecd.org/en/publications/ai-and-skills_f843b352-en.html

OECD & European Union. (2026). *AI literacy framework*. https://ailiteracyframework.org/pdfs/framework_pdf/AILF_en.pdf

Patrinos, H. A. (2024). Estimating the return to schooling using the Mincer equation. *IZA World of Labor*. https://wol.iza.org/articles/estimating-the-return-to-schooling-using-the-mincer-equation/long

Psacharopoulos, G., & Patrinos, H. A. (2018). Returns to investment in education: A decennial review of the global literature. *Education Economics, 26*(5), 445-458. https://www.tandfonline.com/doi/full/10.1080/09645292.2018.1484426

Public First (2026). *AI Global 2026*. https://aiglobal.publicfirst.com/

Rajasekaran, S. et al. (2024). *Digital pathways for education: Enabling greater impact for all*. World Bank, Washington, DC. https://openknowledge.worldbank.org/server/api/core/bitstreams/3c779ab9-1652-4a91-ac17-495d5c23dca3/content

Ravenscroft, T. (2026). *The Essential Skills Advantage: Human Skills in the Age of AI*. Insight Paper. London: Skills Builder Partnership. https://www.skillsbuilder.org/global/file/the-essential-skills-advantage-human-skills-in-an-age-of-ai

Reinitz, B. (2020, June). *Consider the three Ds when talking about digital transformation*. EDUCAUSE Review. https://er.educause.edu/blogs/2020/6/consider-the-three-ds-when-talking-about-digital-transformation

Restless Development, Makerere University and University of Cambridge (2026). *Youth AI Survey 2026: Work, Study and Leisure in the Age of Artificial Intelligence*. https://restlessdevelopment.org/2026/07/work-study-leisure-in-the-age-of-artificial-intelligence/

Schueler, J., Stanwick, J., & Loveder, P. (2017). *A framework to better measure the return on investment from TVET*. NCVER. https://www.ncver.edu.au/__data/assets/pdf_file/0026/861308/A-framework-to-better-measure-the-return-on-investment-from-TVET.pdf

Schultz, T. W. (1961). Investment in human capital. *American Economic Review, 51*(1), 1-17. https://la.utexas.edu/users/hcleaver/330T/350kPEESchultzInvestmentHumanCapital.pdf

Smahel, D., Machackova, H., Mascheroni, G., et al. (2020). *EU Kids Online 2020: Survey results from 19 countries*. EU Kids Online. https://www.eukidsonline.ch/files/Eu-kids-online-2020-international-report.pdf

The World Bank and UNESCO. 2024. *Education Finance Watch 2024*. Washington D.C., Paris: The World Bank and UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000391641

The World Bank, UNESCO and ILO. (2023). *Building better formal TVET systems: Principles and practice in low- and middle-income countries*. Washington D.C., Paris, Geneva: The World Bank, UNESCO, and ILO. http://documents.worldbank.org/curated/en/099071123130516870

Tophel, A., et al. (2025). Towards an AI tutor for undergraduate geotechnical engineering: a comparative study of evaluating the efficiency of large language model application programming interfaces. *Springer Nature Link*. https://link.springer.com/article/10.1007/s10791-025-09580-8

Tony Blair Institute for Global Change. (2024). *The impact of AI on the labour market*. https://institute.global/insights/economic-prosperity/the-impact-of-ai-on-the-labour-market

UNDP. (2019). *Economic return to investment in education and TVET: Micro and macro perspectives*. UNDP. https://files.acquia.undp.org/public/migration/kh/Economic-Return-to-Investment-in-Education-and-TVET-Micro-and-Macro-Perspectives.pdf

UNESCO. (2015). *Recommendation concerning technical and vocational education and training (TVET)*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000245178.locale=en

UNESCO. (2018). *Digital skills critical for jobs and social inclusion*. https://www.unesco.org/en/articles/digital-skills-critical-jobs-and-social-inclusion

UNESCO. (2021). *Recommendations on the Ethics of AI*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000381137

UNESCO. (2023a). *Global education monitoring report 2023: Technology in education – A tool on whose terms?* UNESCO. https://www.unesco.org/gem-report/en/publication/technology

UNESCO. (2023b). *Guidance for generative AI in education and research*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000386693

UNESCO. (2024a). *Global education monitoring report 2024, Pacific: Technology in education – A tool on whose terms?* UNESCO. https://www.unesco.org/gem-report/en/publication/2024-pacific-report-technology-education

UNESCO. (2024c). *AI competency framework for students*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000391105

UNESCO. (2026a). *Education and justice: Learning to build just societies*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000398170/PDF/398170eng.pdf.multi

UNESCO. (2026b). *European Recovery and Resilience Facility. Digital Transformation Collaborative (DTC) Financing Toolkit*. https://www.unesco.org/en/dtc-financing-toolkit/european-recovery-and-resilience-facility-rrf

UNESCO. (2026c). Future proofing TVET: strategies for digital transformation and AI integration. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000398015

UNESCO. (2026d). *Counting the loss: Aid to education in 2024 and 2025* (Global Education Monitoring Report Policy Paper 52). UNESCO. https://www.unesco.org/gem-report/en/publication/counting-loss

UNICEF. (2026). *Snapshot of AI usage and concerns among children and parents*. UNICEF Innocenti. https://www.unicef.org/innocenti/media/13266/file/UNICEF-Innocenti-AI-Brief-2026.pdf

US Census Bureau. (2021). *Women are nearly half of U.S. workforce but only 27% of STEM workers*. https://www.census.gov/library/stories/2021/01/women-making-gains-in-stem-occupations-but-still-underrepresented.html

U.S. National Center for Science and Engineering Statistics. (2026). *STEM Talent: Education, training, and workforce*. National Science Foundation. https://ncses.nsf.gov/pubs/nsb20261/stem-labor

Webb, M. (2020). *The impact of artificial intelligence on the labor market*. https://www.michaelwebb.co/webb_ai.pdf

World Bank. (2025). *Digital Progress and Trends Report 2025. World Bank*. https://www.worldbank.org/en/publication/dptr2025-ai-foundations

World Bank. (2026). *World development report 2026: The promise of artificial intelligence*. World Bank. https://www.worldbank.org/en/publication/wdr2026

World Bank & ILO. (2024). *Active labor market programs improve employment and earnings of young people*. ILO. https://www.ilo.org/sites/default/files/2024-06/WB-Active-Labor-Market-Programs-Improve-Employment-and-Earnings-of-Young-People.pdf

World Bank & UNESCO. (2024). *Education finance watch 2024*. World Bank & UNESCO. https://www.unesco.org/gem-report/en/publication/2024-education-finance-watch

World Economic Forum. (2025a). *The future of jobs report 2025*. WEF. https://reports.weforum.org/docs/WEF_Future_of_Jobs_Report_2025.pdf

World Economic Forum. (2025b). *New economy skills: Unlocking the human advantage* (White paper). World Economic Forum. https://www.weforum.org/publications/new-economy-skills-unlocking-the-human-advantage/

World Economic Forum. (2026). *Shaping the future of learning*. WEF. https://reports.weforum.org/docs/WEF_Shaping_the_Future_of_Learning_2026.pdf

World Economic Forum & LinkedIn. (2025). *Gender parity in the intelligent age*. WEF. https://www.weforum.org/publications/gender-parity-in-the-intelligent-age-2025/

World Health Organization Regional Office for Europe. (2024a). A focus on adolescent social media use and gaming in Europe, central Asia and Canada: Health Behaviour in School-aged Children international report from the 2021/2022 survey. Volume 6. WHO. https://www.who.int/europe/publications/i/item/9789289061322

World Health Organization Regional Office for Europe. (2024b). A focus on adolescent peer violence and bullying in Europe, central Asia and Canada. Health Behaviour in School-aged Children international report from the 2021/2022 survey. Volume 2. WHO. https://www.who.int/europe/publications/i/item/9789289060929

Xu, J., et al. (2025). From occupations to tasks: A new perspective on automatability prediction using BERT. arXiv. https://arxiv.org/abs/2502.09021

Yao et al. (2021). *How much does universal digital learning cost?* UNICEF Innocenti. https://www.unicef.org/innocenti/reports/how-much-does-universal-digital-learning-cost

Ziegler, L. (2024). Skill demand and wages: Evidence from linked vacancy data. In *Research in Labor Economics*. Emerald Publishing. https://www.emerald.com/books/edited-volume/17286/chapter-abstract/94259851/Skill-Demand-and-Wages-Evidence-From-Linked

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Skills Ready: Education, Opportunity and AI

Exploring the socio-economic considerations of AI in education

This report examines the socio-economic returns on investment in digital transformation and artificial intelligence (AI) in education, with particular emphasis on young people and their transition into the labour market. It highlights the increasing importance of digital and AI skills for employment, earnings and economic growth, while identifying persistent inequalities in access, especially across income groups and gender.

The report finds that, although advanced digital and AI skills can generate substantial labour market benefits, evidence on the actual returns from educational investments remains limited. It also explores the opportunities and challenges that AI presents for young people, including its potential impact on entry-level jobs, skills mismatches and employment prospects. The report calls for stronger measurement frameworks, inclusive education and training pathways, and greater collaboration between governments, educational institutions, and the private sector to ensure that digital transformation creates equitable opportunities, supports decent work, and contributes to broader societal well-being.

4 QUALITY EDUCATION

Sustainable Development Goals