SMART TECHNOLOGIES AND THE CHANGING SKILLS LANDSCAPE IN DEVELOPING COUNTRIES

Karishma Banga

Introduction

Developing countries currently face a critical challenge in terms of creating productive employment and skills-development. For instance, 18 million new and productive jobs will need to be created each year through to 2035 to keep up with demographic challenges of youth influx into the sub-Saharan labour market (IMF 2015). Moreover, the Fourth Industrial Revolution is raising concerns of ‘jobless growth’, poor quality informal work and in general a lack of ‘decent work’ – over 1.5 billion people remain in vulnerable employment (ILO 2016). Furthermore, the COVID-19 pandemic has given a rapid boost to the use of smart technologies, with a rise in tele-working, tele-medicines, tele-education, e-commerce and online gaming, etc. This has increased the importance of digital skills in building resilience to shocks such as the pandemic. A survey of 68,574 people in the age group 16–35 from six countries in ASEAN, for instance, reveals that 87% of the respondents increased their usage of at least one digital tool during the pandemic and 42% picked up at least one new digital tool (WEF-ASEAN survey 2020). The number of users on African Development Bank’s Coding for Employment platform (CfE) e-learning platform also witnessed a sharp spike in online learning; the number of users rose by 38.5% to 9,000 within one week (AfDB 2020).

To prepare the youth for productive employment, and for changes in the labour market, developing economies need to adapt to the changing landscape of skills. In an increasingly digitalised economy, employability is being increasingly determined by ‘new skills for the future’ – mainly digital and soft skills. These can be developed through government policies on education and skills-development as well as private sector investment into targeted skills-development. It is also key to note that the relationship between policies and digitalisation is two-way; while policies can boost skills for the digital economy, digitalisation can increase viability and efficiency of policy solutions, such as through online portals for skills-development, mass online courses, EdTech, etc.

This paper proceeds as follows; first, the evidence on the changing landscape of labour markets is discussed at the country level, followed by an examination of the sectoral shifts in employment. Afterwards, a tasks-based framework is presented, which is followed by a discussion on the implications of this framework for labour markets in developed and developing countries. The next section focuses on smart technologies and future skill-needs. The last section concludes and discusses policy implications.
Analyzing the implications of digital technologies on labour markets is a complex issue, since digital technologies can affect employment in a country through national and international pathways, with its impact differing across type of technology considered, sectors, industries and type of tasks (see Figure 7.1). The majority of the evidence on employment effects of automation is from developed countries, with a nascent body of literature on developing countries.

### Smart technologies and country-level employment changes

Analysing the implications of digital technologies on labour markets is a complex issue, since digital technologies can affect employment in a country through national and international pathways, with its impact differing across type of technology considered, sectors, industries and type of tasks (see Figure 7.1). The majority of the evidence on employment effects of automation is from developed countries, with a nascent body of literature on developing countries.

#### Smart technologies and job creation

The potential of digitalisation to create new jobs should not be underestimated. Digital technologies can boost the supply of employment opportunities through a number of channels, including increase in productivity leading to higher output and exports; lower cost of production leading to higher profits which can be re-invested into existing and new product-lines; rise in existing product demand through expansion in customer base using online e-commerce platforms; and lower barriers to entry in the export market – summarised as pathways under Block 1 (Figure 7.1).

Some studies document a rise in jobs due to automation but these are mainly based on data from developed countries. For instance, Gregory et al. (2016) find that computerisation between 1999 and 2010 in the European Union (EU) led to the creation of 11.6 million jobs, not due, as one might expect, to the absence of labour replacing capital but to an increase in product demand and spillover effects in the non-tradable sectors. Similarly, Booz and Company’s (2012) estimates show that digitisation created 19 million jobs in the global economy between 2009 to 2010. Muro and Andes (2015) confirm that developed countries which invest more in robots lose fewer manufacturing jobs than countries which do not.

Even if robotics and automation are substituting labour in certain manufacturing industries, these job losses can be offset by job growth in other complementary manufacturing industries, such as electronics and ICT hardware (WTO 2017), as well as job growth in services sectors.
Smart technologies and changing skills

(Dauth et al. 2017) which are producing and managing these technologies, such as ICT and ICT-enabled services. Even with a manufacturing firm, increasing automation may displace workers performing repetitive tasks in the factory but can create new jobs for more skilled labour in the firm, as well as jobs in the service of automation tools and machinery. However, Autor and Salomons’s (2018) analysis, using country-industry data for 18 developed countries, finds that while automation in one industry indeed displaces employment in that industry, there is lack of evidence for own-industry employment losses being recovered in other sectors. Direct employment losses are offset to some extent by indirect employment gains in customer industries and through increases in aggregate demand (Autor and Salomons 2018). A key drawback in some of the studies that examine the impact of automation on employment is that the labour market is assumed to be frictionless (see, for instance, Autor et al. 2003; Zeira 1998). This implies that a firm’s decision to automate is solely based on the relative price of labour versus technology. Recent evidence reveals that due to frictions in the labour market, workers find it difficult to adjust to industry-level import shocks, leading to high costs of job losses and unemployment, particularly for those with low initial wage levels (Autor et al. 2014). Labour market frictions also differ across countries; labour mobility costs are much higher in developing countries as compared to developed countries (Hollweg et al. 2014).

Smart technologies and job destruction

Some studies find automation to have a labour-substituting effect – that is, automation can displace jobs and substitute labour, affecting overall employment negatively (see, for instance, Frey and Osborne 2017; Bowles 2014; Acemoglu and Restrepo 2017). Examining the impact of computerisation on employment, Frey and Osborne (2017) find that 47% of the jobs in US are at risk of being automated. Using the same methodology, Bowles (2014) finds that 40–60% of the workforce in EU can be displaced by technological changes, with particularly strong effects in labour markets of Romania, Portugal, Greece and Bulgaria, while 57% of jobs in the OECD are at risk of being automated (Oxford Martin School 2016). Some studies, such as Frey and Rahbari (2016) and World Bank (2016) also report that jobs in developing countries are at risk, with particular threat to the manufacturing sector (Hallward-Driemeier and Nayyar 2017; Schlogl and Sumner 2020). Estimates of jobs losses are as high as 69% in India and 77% in China (Oxford Martin School 2016).

A serious drawback of some of these studies is that they assume that occupations as a whole can be automated away. For instance, Frey and Osborne (2017) use a binary categorisation of occupations in their paper, automatable occupations and non-automatable occupations. There is a significant variability in tasks within each occupation, with certain tasks and activities in a job susceptible to automation, while others are not, implying that automatability of jobs is not a binary characteristic (Autor and Handel 2013; Willcocks 2020). A better approach when examining the employment impact of digitalisation is therefore to analyse the task content of individual jobs. On breaking down occupation into tasks that have different levels of automatability, the share of jobs that can be automated in the OECD countries falls to 9% in the US and between 6 to 12% in the OECD, with significant differences across countries depending on regulation, behaviour of users, economic and technical feasibility and labour market dynamics (Arntz et al. 2016).

More recently, McKinsey (2017) examines the potential impact of automation in roughly 2,000 work activities for more than 800 occupations, across developed and developing countries (based on the US labour market data). Assessing the ability of robots in sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities, and
physical capabilities’, it is found that only a small percentage (less than 5%) of occupations can be fully automated, although roughly 50% of work activities in almost all occupations can be automated using current digital technologies. Building on this, Manyika et al. (2017) estimate that by 2030, roughly 3–14% of the global workforce will need to switch occupational categories. While some work activities across all skills-levels can be automated, automation is likely to affect lower-skilled workers more, particularly those involved in the manufacturing sector (McKinsey 2017). Sectoral composition of economic activity is key to understanding economic development (Herrendorf et al. 2014). The national and international pathways discussed earlier are likely to affect employment differently across sectors, industries and tasks (Blocks 3 and 4). For instance, while the manufacturing sector overall is the most susceptible to automation, the rate of automation will differ across industries, depending on technological and economic feasibility. This is discussed further in the section to follow.

In conclusion, there is no consensus that emerges from the literature on automation and employment. Studies use different types of data and methodologies across different regions, with some studies focusing more explicitly on employment impact, acknowledging that estimation of probability/potential of technical automation does not equate with job losses (Parschau and Hauge 2020).

Smart technologies; sectoral shifts in employment

Compared to developed countries, developing economies have a larger agricultural sector, lower shares of employment and value-added in industry and manufacturing, as well as a large informal service sector (Schlogl and Sumner 2020). Smart technologies in agriculture can play a critical role in boosting job creation through increased productivity, value-addition and diversification of functions, increased regional trade, formalisation of work and increased opportunities for women and youth (Krishnan et al. 2020). For instance, use of digital platforms in agricultural value chain and collection of data histories can help in keeping records of creditworthiness of farmers, youth and women who previously may not have been eligible for working capital or personal loans, bringing traditionally marginalised sections of the society into more formal work setting (ibid.). However, it is critical to note that a persistent gendered divide in access to digital technologies can exacerbate the gendered divide in employment. A large proportion of women in developing countries work in the agricultural sector – for instance, 76% in Kenya and 84% in Rwanda – but continue to be marginalised as a result of socio-cultural norms that curb their basic rights and entitlements (such as land ownership), lack of access to the internet, basic skills and education (Commonwealth Secretariat 2020).

In addition to a gendered digital divide in ‘access’ to smart technologies, some studies report a digital divide between men and women in the ‘use’ of these technologies. For instance, a survey of 821 Ugandan farmers shows that female farmers have lower access to digital platforms than men, but even on these platforms, female farmers are lagging in internet access, access to credit and formal work opportunities and access to productivity-enhancing services (ODI 2020). This is linked to lower ownership of mobile phones, lower education and lower digital skills-level in women compared to men (ibid.). In fact, the gendered digital skills-divide is quite stark between developed and developing countries; for instance, while roughly 60% of the female population in the UK can conduct the basic function of copying or moving a file or a folder on the computer, this falls down to as low as 2.9% of the female population in Pakistan who can carry out this basic ICT function (Commonwealth Secretariat 2020). Women also have a lower access to financial services, particularly through mobile technology (Hunt and Samman 2016). Women are 14% less likely to own a mobile phone as compared to men, which
translates into 200 million fewer women than men owning mobile phones in low- and middle-income countries (GSMA 2016).

Moving labour and other resources away from lower productivity sectors, such as agriculture, to higher productivity sectors, such as manufacturing and services, has been labelled as structural change or transformation, including through adoption of new technologies (Mc Millan et al. 2017). Manufacturing-led development has been historically used as a stepping-stone for job creation in developing countries. However, barring a small group of Asian economies, the share of manufacturing value-added in GDP has been declining in developing economies, as a result of structural changes, changing global demand and technological progress – also known as ‘premature de-industrialisation’ (Rodrik 2013). Compared to the services and agriculture sectors, the manufacturing sector is more intensive in ‘routine’ tasks (OECD 2016), which are more easily codifiable and therefore easier to automate. In line with this, the World Economic Forum (WEF) Job Survey (2016) predicts an overall decline of 1.6% in manufacturing and production employment in the period 2015–2020, largely driven by labour-substituting technologies (across developed and developing countries), with 3D printing expected to reduce employment by 3.5%, followed by the changing nature of work (−3%), new energy supplies and robotics. However, these estimates need to be treated with caution since they do not account for labour-complementing productivity improvements through digital technologies, such as robotics. A survey by Capgemini Worldwide1 (2017) in the United States, the United Kingdom, France, Germany, Italy, Sweden, China and India finds that 76% of manufacturers already have an ongoing ‘smart factory’ initiative or are working on one. These smart factories operate on Industrial Internet of Things (IoT), a digital technology that is expected to have a major impact on the landscape of manufacturing. It allows scaling up of interconnected manufacturing, where machinery and equipment communicate with each other through the internet, without a human operator. Such IoT-based manufacturing will require transmission of data across the entire production chain, indicating the increasingly important role of ICT services in the manufacturing processes. This also highlights the growing role of data processing services and need for advanced data analytics.

Within the manufacturing sector, investment in automation is taking place at different rates across industries, depending both on technological and economic feasibility. For instance, the deployment of robots in the garments sector, particularly for sewing operations, has been a challenge due to limpness of the fabric and frequent slipping of materials, indicating that the garment industry could be one of the last to be fully digitally automated (Altenburg et al. 2020). Robots in this sector would require more dexterity as compared to other sectors. At the same time, average wages in the garments sector are relatively low compared to the automotive sector, indicating that automation may not be economical.

Comparing the distribution of robot sales across the main industries of selected countries in Figure 7.2, one can observe that robot deployment in the US, UK and China is much more diversified. Robots are being used in all of the following industries: automotive, electrical, chemical, metal products, food and beverage and other which includes apparels, footwear, etc. In contrast, in developing economies of India, South Africa and Mexico, roughly more than 60% of total robot deployment is concentrated just in the automotive sector. Similarly, in Malaysia, 64% of robot deployment is in the electrical/electronical industries.

Focusing on developing Asia’s use of industrial robots, AfDB et al. (2018) confirm that robot deployment is concentrated mainly in capital-intensive manufacturing – which has relatively

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1 A Paris-based multinational information technology consulting corporation.
low employment levels to begin with. As per their report, while the electrical/electronics sector and automotive sector each accounted for 39% of total robot use in 2015, these sectors accounted for only 9.2% and 4.2% of total manufacturing employment, respectively. In contrast, textiles, apparel and leather combined accounted for only 0.1% of robot usage in 2015, but 19.2% of total manufacturing employment. Given that robot usage is concentrated in sectors with relatively low employment, AfDB et al. (2018) point out that concerns about robots replacing workers may be overstated. Furthermore, labour displacement in developing economies is restricted by the low elasticity of factor substitution (Dao et al. 2017). Globally, industries of paper and paper products, wood and wood products, basic metals, food, beverage and tobacco, and textiles and garments are less affected by global technological changes (Hallward-Driemeier and Nayyar 2017). Developing countries, which are still at nascent stages of installing smart technologies, therefore have a window of opportunity in these sectors, which will still require workforce with traditional industrial skills.

But how long will this window of opportunity last? Although it might take longer compared to developed economies, the relative price of investment goods is eventually likely to fall in developing economies due to continuous and significant advances in technical feasibility of digital technologies and falling capital costs. Banga and Velde (2018a) demonstrate this for the case of the furniture industry; the authors find that while a robot in the US will become cheaper than labour in the US furniture manufacturing industry by 2023, a robot in the Kenyan furniture manufacturing will become cheaper than Kenyan labour more than a decade later—in 2034. Moreover, by 2033, operating a robot in the US becomes cheaper than Kenyan labour, signalling the possible re-shoring of furniture manufacturing tasks to the US around this time.

Smart technologies and shifting patterns of globalisation question the potential of manufacturing-led development for job creation, particularly for developing countries. A strand of literature has subsequently emerged examining the role of services-led economic transformation.

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2 These estimates are based on relative prices of operating a robot and per unit cost of labour. Labour productivity increases over time are accounted for but do not include other factors such as transportation and time to market costs.
Smart technologies are opening up new avenues of value-added in the services sector, including in IT or IT-enabled services, such as business and financial services (Newfarmer et al. 2019; Gollin 2018). In African countries, for instance, mobile telephony and mobile banking have already achieved some successes, and other services sectors of potential include social, education and healthcare sectors, as well as tourism and infrastructure construction.

However, a services-led development model may not be employment-intensive; highly productive and tradable services, such as IT services, require highly skilled workers, while non-tradeable services, such as social care and other personal services, are neither highly value-adding in nature nor scalable (Schlogl and Sumner 2020). Moreover, in some services sectors as well, digital technologies are found to be employment reducing. For instance, mobile internet and cloud technology is predicted to reduce employment by roughly 3.9% in installation and maintenance, and by 5.82% in office and administrative work (WEF 2016). In office and administrative work, virtual assistants are rapidly changing the role or tasks provided by secretaries, particularly in small- and medium-sized enterprises. While traditionally, secretaries have worked in an office setting, virtual assistants are independent contractors or employees who can remotely offer many secretarial services, including office services such as calendar management, documents and filing support, as well as technical services such as social media support, email marketing, transcription, etc. Tasks in financial services, such as data entry and accounting and filing claims as well as manual, clerical, logistical tasks in transportation and storage, inventory management and back-office processing face high exposure to routinisation.

Overall, services-led development tends to require relatively high skills, particularly IT services, which further needs long-term, steady investments in education, infrastructure, institutions and governance. A more balanced approach in developing countries, which incorporates services, natural resources, agriculture and some manufacturing, may therefore be important. This seems to be particularly relevant for Africa, where 60% of the population works in agriculture; natural resources are in abundance; and digital services are probably only realistic for the better-educated segments of the labour market.

Towards a tasks-based framework for skills-analysis

From the previous sections, an important point emerges around shifting the focus from ‘automatability of jobs’ to ‘automatability of tasks’ for understanding future skill-needs in developing countries. The underlying assumption in some studies that occupations as a whole can be automated away may result in overestimating job losses, since there is a great variability in the tasks within each occupation, which is not accounted for in studies of Frey and Osborne and others who rely on the same methodology (Autor and Handel 2013).

Skill requirements across types of tasks can be understood using the skills-tasks matrix, developed by Banga and te Velde (2018b) and presented in Figure 7.3. Tasks can be classified as routine or non-routine and manual or cognitive. Different combinations of these tasks’ categories determine the associated skill-needs:

- The first combination is routine-manual tasks; physical tasks which follow explicit rules and are easier to codify. Examples include operating machinery, carpentry and constructions, performed mainly by middle-skilled workers with physical skills. These tasks are repetitive and do not involve much analytical thinking, and therefore are being increasingly automated. Some routine manual tasks require hand dexterity, such as stitching in garments, which cannot yet be easily performed by robots.
The second combination is routine-cognitive tasks. Compared to routine-manual tasks, these tasks are associated with higher education levels, reading and writing capabilities, as well as more developed cognitive abilities, such as analytical and critical thinking, logical and mathematical reasoning and managing. Routine-cognitive tasks are also performed mostly by middle-skilled workers such as bookkeepers, secretaries, bank tellers and clerks, and are being automated at a fast rate. For example, deployment of self-checkout counters instead of cashiers in stores, and free business management software such as Money Manager EX, TurboCASH and so on.

Non-routine manual tasks are those that either involve agile physical skills (such as operating a vehicle) or ‘soft’ skills (such as interpersonal skills, socio-emotional skills, or empathetic skills). These tasks relate more to service occupations such as nursing, childcare, janitorial work, security work, etc. These tasks, generally performed by low-skilled workers, do not follow any set pattern of rules and require tacit knowledge or personal interactions which are hard to automate.

Non-routine cognitive tasks require job-neutral ‘hard’ skills (measurable skills) such as digital skills (collecting information from online sources, data analysis, etc.) and job-neutral ‘soft’ skills, such as interpersonal skills, managerial skills, analytical thinking and creative-thinking skills. They can also involve job-specific skills, such as legal writing, coding and programming, healthcare, education and training, professional and technical services.

With the rise of smart technologies, the demand for labour in non-routine cognitive tasks is likely to increase. The demand for workers performing non-routine tasks has been on an increasing trend in a number of economies; since the 2000s, the employment share of occupations intensive in non-routine cognitive skills (such as analytical and critical thinking) and socio-emotional skills has increased from 19 to 23% in emerging economies, and from 33 to 41% in advanced economies (World Development Report 2019). Examining 13 major developed and emerging economies, WEF (2016) finds that the percentage of jobs requiring cognitive abilities as a core skill is expected to rise by 15% between 2015–2020. Furthermore, among all the
jobs requiring cognitive abilities as part of their core skill sets, 52% of them do not have such
requirements now but are expected to experience increasing demand for cognitive abilities by
2020 (WEF 2016).

Smart technologies and ‘polarisation’ of skills?

From the previous section, it is clear that there is no consensus in the literature on the impact of
automation on employment. Several studies have, however, established an increase in demand
for labour in non-routine tasks linked to rise in smart technologies. A strand of literature on
developed countries argues that automation has led to ‘labour market polarisation’ or ‘hollowing
out’ of the middle-skilled workforce, with increasing demand for high-skilled and low-skilled
labour relative to middle-skilled workers (see Autor et al. 2006; Goos and Manning 2007; Autor
and Dorn 2013; Goos et al. 2014; Beaudry et al. 2016). The main reason for this polarisation is
‘routinisation’; middle-skilled workers3 are engaged in occupations that consist of routine tasks
that can be more easily automated. In contrast, high-skilled workers perform non-routine tasks,
complementary to new technologies, such as research and development, managing, designing
(Beaudry et al. 2016), and low-skilled workers perform non-routine manual tasks that are hard
to automate, such as nursing and childcare. Highly paid skilled work has in turn raised the
demand for low-paid services, reinforcing polarisation of occupations into ‘lovely’ and ‘lousy’
jobs in developed countries (Goos and Manning 2007). These low-skilled services include non-
routine tasks such as catering, construction, cleaning and childcare, which do not follow precise
procedures and are therefore much harder to automate (Autor and Dorn 2013). Many of these
services, however, remain the least educated and least paid categories of employment.

Job polarisation due to routinisation of tasks has been mainly documented for developed
economies (see, for instance, Spitz-Oener 2006; Autor and Dorn 2013; Michaels et al. 2014;
Goos et al. 2014; Ikenaga and Kamibayashi 2016), with the degree of dislocation of middle-
skilled workers varying significantly. For developing countries, the literature on job polarisa-
tion is limited and there appears to be no single picture that has emerged. There is evidence
of job polarisation in Chile during the 2000s (Messina et al. 2016) and in Brazil and Mexico
(Maloney and Molina 2016). Some studies, such as World Bank (2016) and Reijnders and De
Vries’s (2017) find declining shares of middle-skilled workers in some developing countries, and
conclude that as being indicative of job polarisation. As per World Bank (2016), some countries,
such as Malaysia and Uganda, witnessed declining share of middle-skilled workers in the period
1995–2012, but the rate of decline is lower in developing countries – at 0.39% as opposed to
0.59% a year in developed countries (World Bank 2016). Focusing on Asian economies,
AfDB et al. (2018) find that between 2005–2015, the share of jobs intensive in non-routine4
tasks increased, while routine-intensive jobs declined. ADB’s (2018) analysis of employment
trends in five developing Asian economies (India, Indonesia, the Philippines, Thailand, and
Viet Nam) shows that over the past decade, annual expansion of employment in jobs intensive
in non-routine cognitive tasks, social interactions and the use of ICT was 2.6% faster than
total employment. Figure 7.4 shows employment growth by task-intensity and type across the

3 Middle-skilled occupations are those that are intensive in routine cognitive and manual skills, such as clerks, crafts
and related workers, plant and machine operators. In contrast, high-skilled occupations are intensive in non-
routine cognitive and interpersonal skills such as technicians and professionals, while low-skilled occupations are
intensive in non-routine manual skills such as sales and service workers.

4 Classification into routine and non-routine is based on Autor and Dorn (2013) and excludes agricultural
occupations.
five Asian economies; employment growth is observed to be positive in cognitive tasks (both routine and non-routine) and tasks which are intensive in social interaction and ICT. Rapid digital progress in some sectors accompanied by a proliferation of low-paid service jobs has also been documented in Turner (2018). Detailed analysis of occupation titles in three Asian countries – Malaysia, Philippines and India5 – by the ADB (2018) further reveals that new job titles have emerged to handle new technologies, particularly in occupations of ICT operations and user support technicians, architect and designers, software application developers and analysts, medical and pharmaceutical technicians, electronics and telecommunications installers, sales and marketing professionals as well as database and network professionals and other health associate professionals. In contrast, manual jobs have experienced limited employment and wage growth, contributing to rising inequality (ibid.).

Studies that use declining shares of middle-skilled workers to show job polarisation, such as World Bank (2016), suffer from the serious drawback of assuming broad groups of middle-skilled occupations being routine-intensive (Das and Hilgenstock 2018). Within occupations, there is heterogeneity in routine-intensity of tasks, which needs to be accounted for in order to avoid overestimation of the decline in middle-skilled occupations (ibid.). Moreover, for routinisation to result in polarisation, a significant share of the economy has to be engaged in middle-skilled occupations (Das and Hilgenstock 2018), which is not the case for developing

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5 Data for Malaysia is for the year 2008, India, 2015; Philippines, 2012.
Smart technologies and changing skills

In the age of smart technologies, there is likely to be growth in non-routine cognitive tasks with developed countries experiencing job-polarisation, explained further in the following sections. While the evidence of job-polarisation in the case of developing countries is mixed, it is clear that smart technologies will increasingly require digital and soft skills. We explore these categories, and how developing economies are faring in these skills, in more detail.

As demonstrated in Figure 7.3, under the block of non-routine cognitive tasks, digital skills can be categorised as job-neutral or job-specific. These skills range from basic to intermediate levels. Basic job-neutral skills are those that are neutral to the industry of the worker and are important for workers to function at a minimum level in a digital economy. These skills can be further broken down into hardware skills – the skills to operate a computer and touch-screen smartphones, as well as software/online skills such as emailing and searching the internet which can help gain access to information and people (ITU 2018). Intermediate job-neutral digital skills refer to skills for engaging with internet and digital technologies in a more productive manner that can be used across a wide range of digital tasks. Examples include skills to use computer technology (for instance, use of Microsoft® Office and PowerPoint), digital design (User Interface design, Photoshop, etc.), digital marketing (use of social media and electronic platforms) and data analytics and storage, as well as secure use of the internet to carry out such tasks (ITU 2018). Job-specific digital skills are advanced or specialised technical skills, such as computer programming, network management, coding, big data analytics, cryptography, and so on. Such skills are mainly acquired through advanced formal education but can also be learnt from other options such as incubators, boot camps, etc. (ITU 2018). Banga and te Velde (2018b) show that the share of ICT professionals – such as web programmers, coders etc. – in total employment is much lower in developing economies compared to the US; the share of ICT professionals in total employment is around 2.4% in the US, but as low as 0.18 and 0.04% in developing economies of Thailand and Indonesia respectively.

Table 7.1 presents ITU data on the percentage of population across a range of low-, middle- and high-income countries, across types of skills. It is observed that while over 60% of the population in high-income countries of UK and Germany have basic digital skills of copying/moving a file or folder or using copy/paste tools, only 3–5% of the populations in Pakistan, Zimbabwe and Sudan have basic digital skills. Similarly, over 30% of the population in Germany, Singapore, UK and Italy can use basic arithmetic formulas on a spreadsheet but this falls to below 10% in countries of Cambodia, Niger, Zimbabwe, Sudan, Pakistan, Jamaica and Tunisia. A wide variation is also noticed in terms of intermediate digital skills across income economies, where jobs tend to be more concentrated in industries with low susceptibility to automation (ILO 2014; Maloney and Molina 2016). Roughly, 40% of the workforce in developing countries continues to be employed in the primary sector (ILO 2014). Furthermore, a key driver of routinisation-induced polarisation is the decline in the relative price of investment goods, which is more of a developed country phenomenon (Dao et al. 2017). In contrast to the evidence on job polarisation in developed countries, there is some evidence of smart technologies shifting employment towards less-skilled workers in developing countries. For example, digital technologies in Chilean manufacturing in the period 2007–2013 shifted employment structure towards less skilled workers performing routine and manual tasks (Almeida et al. 2017). In middle-income countries in Europe, such as in Bulgaria and Romania, while the demand for non-routine cognitive and interpersonal work is increasing, there is no increase in demand for low-skilled non-routine manual work (Gorka et al. 2017).
Table 7.1 ICT skills, by type of skill (% of population)

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<td>Zimbabwe</td>
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<td>7.7</td>
<td>3.6</td>
<td>31.3</td>
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<td>1.8</td>
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<td>6.2</td>
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<td>information within a document</td>
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<td>Using basic arithmetic</td>
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<td>2.8</td>
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<td>2.9</td>
<td>3.2</td>
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<td></td>
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<td>installing and configuring</td>
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<td>Creating electronic</td>
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<td>presentations with presentation</td>
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<td>software</td>
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<td>Transferring files between a</td>
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<td>computer and other devices</td>
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<td>Writing a computer program</td>
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<td>using a specialised</td>
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<td>programming language</td>
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Source: ITU (2018)
status. In terms of advanced digital skills, it is observed that 6–8% of the population in Spain, UK, Singapore and Malaysia are using the internet for writing a computer programme using specialised programming language, but this falls to as low as 0.6% in Zimbabwe, 0.9% in Nigeria and 0.1% in Cambodia.

Soft skills refer to interpersonal skills, managerial skills, analytical, critical thinking and problem-solving skills as well as creative skills and adaptive skills. Employers in Benin, Liberia, Malawi and Zambia suggest technical skills, teamwork, communication and problem-solving skills are the most important set of skills for the future (World Bank 2019). Even advanced digital technologies can require soft skills. For instance, 3D printing involves the knowledge of computer-aided design and ‘additive manufacturing’, advanced digital skills of 3D modelling but also soft skills of problem-solving, critical thinking and creative designing. Developing countries continue to lag behind in soft skills compared to developed countries (Banga and te Velde 2018b).

**Conclusion and policy implications**

A number of important insights have emerged from this study. First, automation may create new employment opportunities, replace labour in certain tasks and also change the role of workers in certain occupations. The rate of automation differs across countries and sectors, depending on technological and economic feasibility; the impact of automation on the labour market also differs across countries, depending on a number of factors, including globalisation, new product demand, occupational structure in employment, labour frictions, institutional differences affecting relative wages and so on. Routinisation has led to labour market polarisation in developed economies. But there is less evidence of declining employment shares of middle-skilled workers in developing economies, possibly owing to labour being more concentrated in low-skilled and low-routine occupations as well as the slower decline in the relative price of investment. The rate of polarisation also varies across developing countries.

However, given the fast pace of technical advances and the falling cost of capital equipment, polarisation is a possible scenario for developing economies in the future. Given that digitalisation affects both employment and employment structures, it is important to identify what skills are likely to be in demand in the future. In the context of the digital economy, the study identifies core skills that can directly increase the competitiveness of the workforce: (1) job-neutral digital skills; (2) job-specific digital skills; and (3) job-neutral soft skills such as communication, management, analytical and critical thinking and creativity.

Complementary actions at different levels are needed for developing countries to close or reduce the digital and soft-skills gap with regards to developed countries. This will require addressing both supply-side and demand-side challenges to skills-development. On the supply side, there is a need to incorporate digital literacy and basic ICT skills at the primary and lower-secondary level of education, and increasing Technical and Vocational Education and Training (TVET) enrolment at the upper-secondary and tertiary levels to increase provision of intermediate to advanced digital skills and soft skills (Banga and te Velde 2019). Non-formal TVET can be extended through apprenticeships and Recognition of Prior Learning (RPL). With increasing deployment of smart technologies in production, employed-led training is emerging as an important channel of skills-supply, due to inability of TVET curricula to catch up with the fast pace of technological change (Wolter and Ryan 2011) and lack of effective trainers in TVET with expertise/knowledge of new technologies (ACET-MCF 2019).

Policies that create the right incentives for firms to demand technology and invest in skills-development are also important. This includes policies that facilitate competitive domestic
market, R&D culture, technology transfer, foreign direct investment, upgrading in global value chains, etc. Improving national co-ordinating mechanisms to address systemic failures between the supply and demand for technology and skills is also important. This can be done through collaborations across educational and research institutes, training providers, enterprises and fostering skills diffusion. Some examples of these intermediate institutions include industry associations, R&D consortia and technology hubs or parks, in addition to online portals and platforms that can help in reduce information gaps across the demand and supply of skills (Banga and te Velde 2019).

With limited budgets, countries may need to make trade-offs. An important trade-off is between today’s workers – a large percentage of whom lack basic digital and soft skills – and the future labour force for which early investments into digital and soft skills should be prioritised given the relatively higher returns (World Bank 2019). Ultimately, the relative weight placed on education policy priorities will depend on a country’s cultural, political and economic context. For instance, countries which are more digitalised may choose to direct their resources in reorienting secondary and tertiary TVET towards digital skills, while those still at nascent stages may choose to focus on expanding basic digital literacy in the population. Coherence between education, skills development and other policies will further require solid institutional structures and clear mapping of responsibilities, better dialogue and effective co-ordination.

Identifying future skill-needs and channels of skills-development have become more important now than ever. This chapter showed that increasing use of smart technologies has significantly changed employment structures across countries and skills landscape. The COVID-19 pandemic is likely to accelerate the use of smart technologies across the globe, with businesses shifting online, people working from home, and students learning remotely. However, the pandemic also threatens to exacerbate the existing digital skills-divide across countries. Key areas of future research there include identifying how the pandemic is affecting deployment of smart technologies in global production; its subsequent effects on employment patterns and skills structures; examining whether it is exacerbating or creating job polarisation in developing countries; and how skills-development policies can contribute to inclusive post-crisis recovery.

References


Smart technologies and changing skills


The International Federation of Robotics (IFR) database, 2017. Available at https://ifr.org/


