Skill needs for the future

Background Paper

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Pathways for Prosperity Commission
Technology & Inclusive Development

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This paper is part of a series of background papers on technological change and inclusive development, bringing together evidence, ideas and research to feed into the commission's thinking. The views and positions expressed in this paper are those of the author and do not represent the commission.

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Extended abstract

The digital economy is developing rapidly but unevenly across countries, firms, and people. While the rapid deployment of digital technologies such as robotics and 3D printing can usher in a new era of productivity, create efficiencies and generate jobs. Given the dynamic impact of digitalisation on the labour market – both in terms of employment and occupational structure – it is becoming increasingly important for developing economies to adapt to the rapidly changing skills landscape. To become more competitive, developing economies need to re-equip and re-skill their workforce with skills that are going to become important in the future. The main aim of this study is to identify these future skills.

There is a digital divide between developing and developed countries, both in terms of access and use of digital technologies. To close this digital divide, the study puts forward four areas that need to be addressed in developing economies:

1. lowering the cost of capital, energy and financing;
2. improving basic infrastructure such as reliable access to power supply, improving roads, ports, postal systems, etc – as well as digital infrastructure such as high-speed internet and interoperability;
3. developing a digital identification system; and
4. improving absorptive capacity through targeted skills development.

There is much discussion around the jobs that are susceptible to automation. Digital technologies are likely to make some jobs redundant, but are more likely to affect overall jobs through substituting specific tasks in a job, freeing up workers to perform other tasks or new tasks that will require new skills. The impact of such technologies on the labour market will differ across countries, depending on economic and technical feasibility, regulation, behaviour of users and labour market dynamics.

Reviewing the evidence on developed economies, the study concludes that developing countries are also likely to experience a change in the structure of employment, depending on globalisation, digitalisation, changes in product demand and institutional differences. While there is significant evidence of 'labour market polarisation' in developed countries – mainly as a result of routinisation of tasks performed by middle-skilled workers – evidence for developing economies is mixed. One of the factors behind the effect of routinisation on polarisation is the decline in the relative price of investment goods, which differs across countries.

Within developing economies, the exposure to routinisation also varies across sectors. Agricultural occupations such as skilled agriculture, forestry and fishery workers are the least intensive in routine tasks. Services sectors such as accommodation, retail and sales are also less exposed to routinisation – tasks such as sales require inter-personal and communication skills, which are harder to automate. By contrast, manufacturing tasks can be automated at a faster rate. Within the manufacturing sector, the rate of automation depends both on technological and economic feasibility, with industries being automated at different rates. Robot deployment in the US, UK and

China is much more diversified across industries, but is concentrated mainly in capital-intensive manufacturing in Developing Asia – which has relatively low employment levels to begin with. In the case of India, South Africa and Mexico, robot deployment is concentrated in the automotive sector.

The future skills largely depend on what tasks remain in demand or are increasingly demanded in the digital economy. To unpack the different skills needs across types of tasks, the study builds a Skills–Tasks matrix, which distinguishes between routine-manual tasks, routine-cognitive tasks, non-routine manual tasks and non-routine cognitive tasks. Analysis undertaken in this study indicates changing occupational structure across developing economies, with relatively higher future job growth expected in non-routine cognitive tasks.

In the context of the digital economy, the study identifies 'core skills' which can directly increase competitiveness of the workforce, and 'ancillary skills' which either remain relevant or support the digital economy but do not directly contribute to it. Core skills that need to be developed include:

a) job-neutral digital skills;
b) job-specific digital skills; and
c) job-neutral soft skills such as communication, management, analytical and critical thinking and creativity.

Ancillary skills that can support the digital economy include: a) physical skills that require dexterity; and b) socio-emotional and interpersonal skills for low-skilled service and sales occupations.

The study assesses current skills-readiness of developing economies under different task categories, using information on education, ICT employment and skills shortages. It is found that developing countries are significantly less digitally ready, in part because their technical tertiary education and vocational training rates are lagging. They also lag behind in analytical and interpersonal skills. Skills shortages have increased over time in some African countries. In Romania and South Africa, there appears to be an overall skills surplus of technical skills, but a skills shortage of problem-solving skills, social skills and critical-thinking skills.

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1. Introduction

The digital economy is developing rapidly but unevenly across countries, firms, and people. While the rapid deployment of digital technologies such as robotics and 3D printing can usher in a new era of productivity, create efficiencies and generate jobs, it is also rapidly changing the skills needs. As digitalisation increases, some jobs in developing countries may be taken away as a result of reshoring of manufacturing activities to the developed parts (with lower cost of capital). But new jobs will also be created, linked to the demand for new products and opportunities – for instance, through e-commerce – while existing jobs are also likely to be transformed, generating the demand for different, and possibly new, skills in the workforce.

With the tendency of digital technologies to replace labour performing routine tasks, there has been a movement of labour in developed economies towards non-routine cognitive tasks as well as non-routine manual tasks that are harder to automate. A number of studies have examined labour market polarisation in developed economies and found evidence of 'hollowing out' of the middle-skilled jobs, leaving the middle-skilled labour the most affected. Fewer studies have examined the existence of job polarisation in the context of developing economies, and those that do exist provide mixed evidence. While labour market polarisation has been observed in some developing countries, the rate of polarisation is lower compared to developed countries, possibly due to developing country labour being more concentrated in low-skilled, low-routine occupations and the slower decline in the relative price of investment in such countries. However, rapid advances in technical feasibility and falling cost of capital could lead to an increase in polarisation over time.

Given the dynamic impact of digitalisation on the labour market – both in terms of employment and occupational structure – it is becoming increasingly important for developing countries to prepare for the digital future by re-equipping and re-skilling their workforce with skills that are going to become important in the future. The main objective of this study, therefore, is to identify the skills that developing countries are going to need in an increasingly digital future. This is done by conducting a literature review and through data analysis relating to how developing economies are faring in the digital economy. We especially focus on the implications of digitalisation for the level and structure of employment, and the likely sectors and tasks that are going to become important in the future.

Section 2 conceptualises the digital economy and uses indicators such as robot density and 3D printing as examples to examine how developing economies are faring in the digital economy. This section also discusses how developing economies can increase their digital-readiness to become more competitive. Section 3 examines the implications of digitalisation on the labour market, both in terms of overall employment and its composition. Section 4 identifies promising sectors and occupations that are likely to attract job growth in the future. Section 5 builds a Skills-Tasks matrix, which helps to 'unpack' the skills needed in different types of tasks, and examines the changing occupational structure in developing economies. Two concepts of skills in the digital economy are identified; 'core' skills that directly contribute to increasing the competitiveness of workforce in the digital economy and 'ancillary skills' that support the digital economy or remain relevant but do not directly contribute to it. Section 6 then assesses the current skills-readiness of developing economies under different task categories, using information on education, ICT employment and skill shortages. Section 7 provides concluding remarks.

2. Digital-readiness in developing countries

The digital economy is broad and complex, encompassing different components. Banga and Te Velde (2018) define digitalisation of the economy as “output enabled through digital transformation”. In their conceptualisation, ‘inputs’ into the digital economy comprise of different digital technologies – such as artificial intelligence and big data – which need ICT infrastructure, including satellites, routers and broadband lines to be operationalised. ‘Output’ in this digital economy comprises: a) digitally-enabled platforms (such as Amazon and Alibaba), applications (for example, fintech applications), consumer services (such as Uber, Spotify) and e-government services; b) digital products, which are either traded physically through e-commerce platforms or electronically transmitted; and c) smart machines such as robots and 3D printers. To operate and function in the digital economy, a digitally enabling environment is also important, bringing into play the role of a supporting institutional and regulatory framework, national innovation systems, digital skills and digital accelerators (for example, perception of the consumers and their behaviour regarding use of digital technologies).

Examining G20 countries in the period 2010–2016, Marcus et al. (2015) find that the digital economy is growing at rate of 10% a year, significantly faster than the overall economy of the G20. Although, the growth in the digital economy has been higher in developing economies – at around 15% to 25% per annum, there is still a significant digital divide in levels of access and use of digital technologies between developing and developed countries. This is true across a range of digital technologies – from something as basic as having access to the internet to something as sophisticated as robotics.

Figures 1 and 2 compare developed and developing economies in terms of their use of robots and 3D printing capabilities respectively. Information on both these indicators is available across selected developed and developing countries and captures important aspects of the digital economy that can make both skilled and unskilled labour more productive.

Figure 1 shows that, in terms of robot density – the number of robots deployed per 10,000 workers – developed countries of South Korea, Japan and the US are ahead of developing countries. Compared to the world average robot density of 74 robots per 10,000 workers, India is using only three robots per 10,000 workers.[1] Similarly, in terms of 3D printing capabilities – measured using AT Kearney’s 3D printing index – developing economies are lagging compared to developed countries, with African economies featuring at the bottom. This index captures the extent to which labour skills, industrial capabilities, governance and economic assets in a country support 3D printing.

[1] Robot densities in countries such as India may be lower due to the abundance of cheap and low-skilled labour, which makes investment in capital-intensive robotics less attractive. This points to the classic problem in understanding the causal impact of skills on technology; the two are mutually dependent. Here, the general point is that developing economies have installed fewer digital technologies.

Figure 1: Robot Density

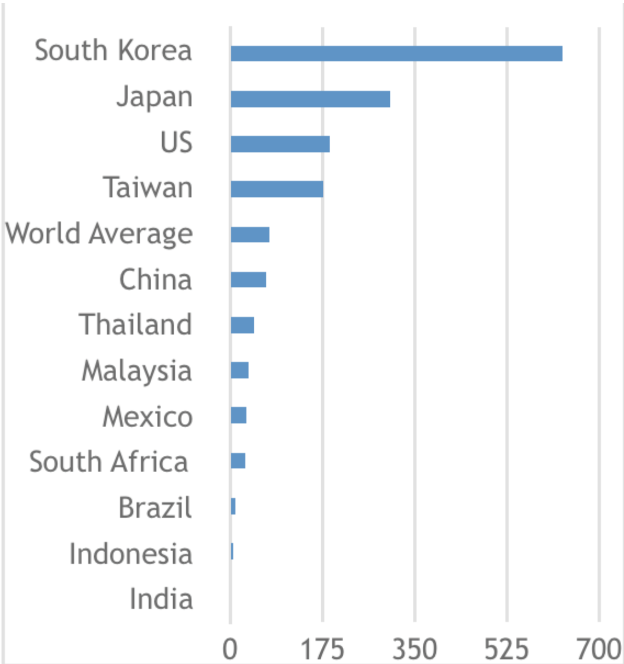
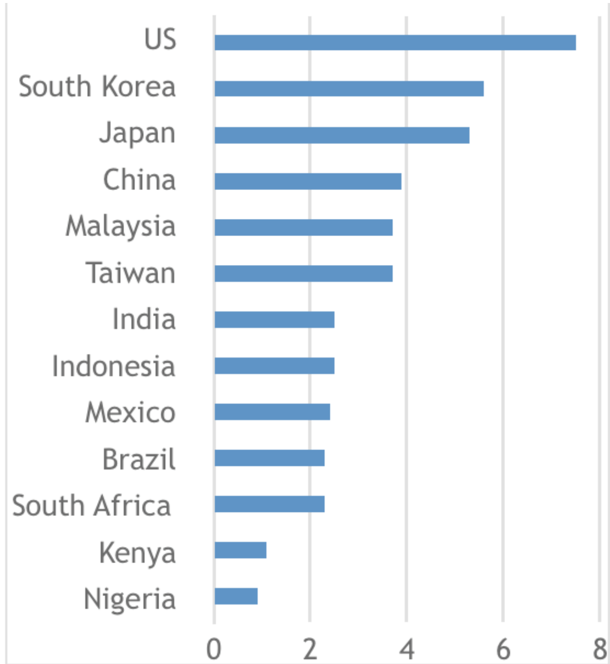


Figure 2: 3D printing index



Source: International Federation of Robotics (IFR) (2017). Data is for 2016. NB: Robot density is number of robots per 10,000 workers.

Source: AT Kearney's (2017) 3D printing index. Data is for 2017.

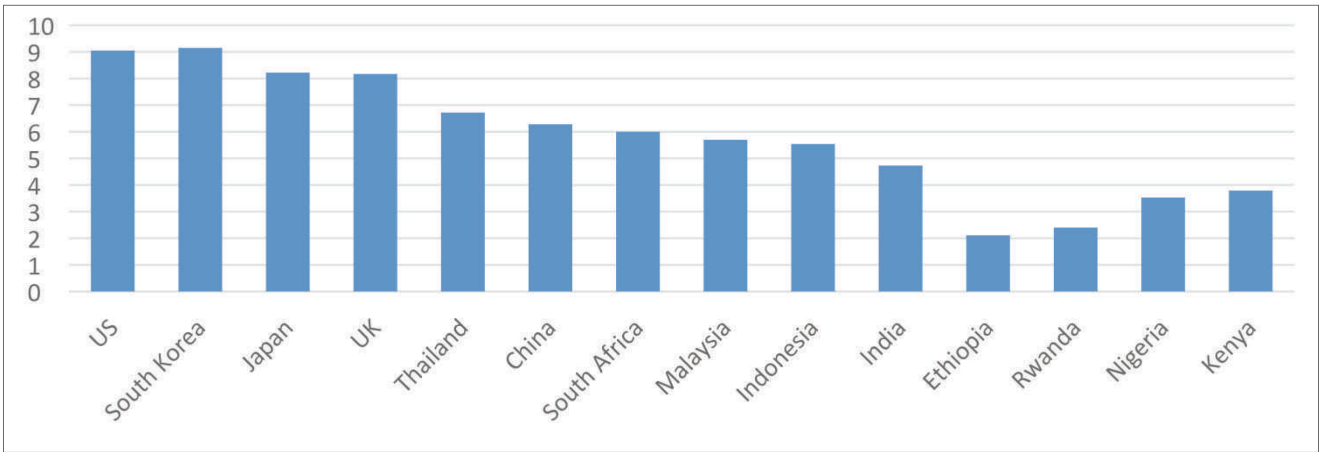
Banga and Te Velde (2018) point to a two-pronged problem for developing economies in increasing competitiveness in the digital economy; not only is the level of digitalisation lower in such countries, but the impact of digitalisation on labour productivity is also lower. The authors find that, while a doubling of the internet penetration rate (measured as the percentage of population that has access to internet) can boost manufacturing labour productivity by roughly 11% in middle-income economies, the impact of the same doubling on low-income economies is only 3%. This gap in the impact of internet on manufacturing labour productivity is also noted for Sub-Saharan Africa (SSA) countries with respect to non-SSA low- and middle-income countries. These results indicate that, even if low-income countries are able to have the same access to digital technologies as middle-income countries, the impact on labour efficiency will still be lower, likely due to the absence of a supportive environment.

To address the digital divide in access and use of digital technologies, a number of issues need to be addressed in developing economies. First and foremost, digital-readiness in developing economies can be improved by *lowering the cost of capital and energy as well as financing*, which is particularly high in African countries, constraining them from investing in digital technologies. Borrowing funds is roughly 40–70% cheaper in developing economies of Asia such as India, China and Thailand compared to African economies (Iarossi, 2009). Using World Bank TCdata360 on access to loans (the ability to get a loan only based on a good business plan and no collateral) in the year 2017, we further find that it is much easier to get a loan in developing economies of China, India, Malaysia and Thailand than in African countries of Nigeria, Kenya, Ethiopia and Malawi.

Second, infrastructure in developing economies needs to be improved and developed. This refers to both *improving basic infrastructure* such as securing a reliable access to power supply, improving roads, ports, postal systems, and so on, as well as *developing digital infrastructure* including high speed internet connectivity, mobile virtual networks and interoperable systems. This will help to create an enabling environment for digital transformation to take place. Third, developing economies can benefit from building a nation-wide *digital identity system*, such as the Aadhaar card in India. A digital identity is the very basis of functioning in a digital economy, and is also a key enabler of access to government benefits, cross-border authentication, digital payments and e-commerce growth.

Most relevant to this paper is the fourth aspect of building digital-readiness – *improving the absorptive capacity* of the developing country firms. This refers to improving the "capability of recognising, assimilating, and applying within internal boundaries external knowledge sources and technologies" (Cohen and Levinthal, 1990). Developing countries, on average, have a less-skilled workforce compared to developed economies and, as a result, have a lower capability of utilising technology efficiently. As shown in Figure 3, developed economies of US, South Korea, Japan and the UK fare well above the developing economies of Asia and Africa on the International Telecommunication Union (ITU) sub-skills index – the ICT Development Index (IDI). This index attempts to capture capabilities or skills important for ICT, and uses information on mean years of schooling, gross secondary enrolment and gross tertiary enrolment.[2]

Figure 3: ITU's IDI sub-skills index across selected developed and developing countries



Source: ITU IDI sub-skills index.

Note: Data is for 2017. Vertical axis shows values for ICT skills index that uses information on mean years of schooling, gross secondary enrolment and gross tertiary enrolment.

[2] ITU's skills sub-index includes three proxy indicators: adult literacy, gross secondary enrolment, and gross tertiary enrolment. The Adult literacy rate has been defined as: "the percentage of population aged 15 years and over who can both read and write with understanding a short simple statement on his/her everyday life." The gross enrolment ratio is defined as: "the total enrolment in a specific level of education, regardless of age, expressed as a percentage of the eligible official school-age population corresponding to the same level of education in a given school-year."

3. The implications of digitalisation for the labour market

Although there is a persistent digital divide, digitalisation is growing globally, bringing with itself a higher level of automation and inter-connectivity into the manufacturing processes and economic landscape. As a result, new tools, technologies and machines are being deployed: there are smart machines coordinating manufacturing; smart service robots collaborating with workers on assembly lines; smart transport systems for delivery and new fintech applications for payments. These changes are expected to have a significant impact on labour demand (Section 3.1), and its composition (Section 3.2).

3.1 Digitalisation and the changing demand for labour

Most studies examining the consequences of digitalisation on employment relate to developed countries. Of these studies, some 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, 2013; Bowles, 2014; Acemoglu and Restrepo, 2017). Examining the impact of computerisation on employment, Frey and Osborne (2013) find that 47% of the jobs in US are at risk. Using the same methodology, Oxford Martin School (2016) finds that 57% of jobs in the OECD, 69% in India and 77% in China are at risk of being automated, while technological change can displace roughly 40–60% of the labour force in EU (Bowles, 2014), particularly affecting job markets of Romania, Portugal, Greece and Bulgaria.

These high estimates have, however, been criticised in the literature for assuming that occupations as a whole can be automated. There is a great variability in the tasks within each occupation, which is not accounted for (Autor and Handel, 2013). Since automation is more likely to make certain tasks in an occupation redundant, rather than the entire occupation itself, a better approach when examining the employment impact of digitalisation is to analyse the task content of individual jobs. On breaking down occupations into tasks that have different levels of automatability, the share of jobs that can be automated in the OECD countries falls to 6–12 %, with significant differences across countries, depending on regulation, behaviour of users, economic and technical feasibility and labour market dynamics (Arnzt et al. 2016).

More recently, Bughin et al.(2017) examine the potential impact of automation in roughly 2,000 work activities – not whole occupations – across developed and developing countries. Assessing the ability of robots in "sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities, and physical capabilities", the authors find 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.

The potential of digitalisation to *create* new jobs should not be underestimated. Digital technologies can boost employment opportunities through a number of channels, including: increase in productivity leading to higher output and exports; lower cost of production leading to new product demand and profits; rise in existing product demand; and lower barriers to entry in the export market (Banga and Te Velde, 2018). Cross-country studies documenting a positive employment impact of automation include Booz and Company (2012) and Muro and Andes (2015), as well as Gregory et al. (2016) for the EU. WTO (2017) further holds that labour being displaced by installing digital technologies in some sectors can be absorbed into sectors that are producing these technologies, as well as into tasks that are complementary to automation and robotics. Increasing deployment of robots in manufacturing, for instance, not only requires more skilled labour in manufacturing but also creates jobs in the service of automation tools and machinery.

Recently, however, using country-industry data for 18 developed countries, Autor and Salomons (2018) show that, while automation in an industry indeed displaces employment in that industry, there is no evidence of these employment losses being recovered in other sectors. Nevertheless, the authors do find that direct employment losses are offset to some extent by indirect employment gains in customer industries and through increases in aggregate demand. It is also important to note that, in some of the studies that examine the impact of automation on employment, the labour market is assumed to be frictionless (see for instance, Autor et al., 2003; Zeira, 1998). This results in a firm's decision to automate being solely dependent on the relative price of labour versus technology. In reality, some developing countries such as India have imperfections in the capital markets as well as high labour market frictions that can significantly reduce labour mobility across sectors. Recent evidence reveals that, due to frictions in the labour market, workers find it difficult to adjust to industry-level import shocks (Autor et al. 2014), leading to very high costs of job losses and unemployment (Jacobson et al., 1993).

3.2 Digitalisation and the changing occupational structure

Tinbergen's pioneering work (1974; 1975) shows that the relative demand for skills in an economy is linked to the skill-bias of technical change; as technology improves, the demand for more 'skilled workers' rises. This model, referred to as the "canonical model" in Acemoglu and Autor (2011), includes only two skills groups (high-skilled and low-skilled workers) performing two distinct and imperfectly substitutable occupations. Technology in this model can either complement the high-skilled workers or the low-skilled workers, with changes in technology capturing skill-biased technical change.

It is important to note that skills and technology do not have a one-way relationship; they are complementary factors that are mutually dependent on each other. Cohen and Levinthal (1990) argue that absorptive capacity and skills are required in the first place to: implement and adapt the new technology; accurately anticipate innovation trends; and capitalise on emerging opportunities and first-mover advantages (Cohen and Levinthal 1994).

Autor et al. (2003) and Acemoglu and Autor (2011) further criticise the canonical model for not systematically distinguishing between skills and tasks, which becomes particularly relevant when workers with a particular skill-level can perform a range of tasks and can alter the set of tasks performed, based on the demands of the job market. More specifically, improvements in ICT have enabled firms to either directly perform or offshore a subset of the tasks previously performed by semi-skilled workers. However, such changes in allocation of skills to tasks remain unaccounted for in the canonical model.

To account for such changes, Acemoglu and Autor (2011) put forward a model in which each worker has either low-, medium- or high-level skills. Firms allocate skills to tasks, based on both the price of the task and the wages of workers in different skills categories. By considering skills (attained from labour), technologies (attained from capital) and offshoring as competing inputs, the model allows for new technologies that may directly replace workers in certain tasks.

Findings of 'labour market polarisation' in a number of recent studies on developed economies lend support to this framework. Labour market polarisation refers to the phenomenon of increasing demand for high-skilled and low-skilled labour relative to middle-skilled workers, often termed as 'hollowing out' of the middle-skilled jobs (see Autor et al. 2006; Goos and Manning 2007; Autor and Dorn 2013; Goos et al. 2014; Beaudry et al. 2016).

The key explanation for polarisation is 'routinisation' that is, middle-skilled workers are engaged in occupations that consist of routine tasks which can be more easily automated. As per Autor et al. (2003), routine tasks "...require methodical repetition of an unwavering procedure... exhaustively specified with programmed instructions and performed by machines". Routine tasks therefore tend to be concentrated in middle-skilled jobs such as machine operators, clerical work and assembly-line workers, where tasks can be more easily codified to be performed by computers. In contrast, high-skilled workers perform non-routine tasks that can complement technology – for instance, research and development and professional services (Beaudry et al. 2016), while low-skilled workers perform non-routine manual tasks that are harder to automate.

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 child care, 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. Despite being a developing country, India is also displaying this developed world phenomenon in which rapid digital progress in some sectors is accompanied by the proliferation of low-paid service jobs in activities which are, at least for now, difficult to automate (Turner, 2018).

In some cases, technological change can lead to deskilling of occupations much before the occupations themselves disappear. Consider, for instance, London cab drivers who traditionally have had to pass a comprehensive test to get a licence for driving that involved memorising 25,000 London streets (German, 2018). Compare this to the current scenario in which introduction of navigation and GPS systems, and platforms such as Uber, mean that drivers no longer need the skill of spatial cognition. The key expertise necessary to do the job is now provided by software, that is, step-by-step navigational instructions (Robinson, 2017), which has lowered the barriers to entry into driving and allowed less-skilled workers to enter the occupation.[3] At the same time, skilled jobs such as programmers and app designers who create online platforms such as Uber are increasing.

[3] In countries without a strong labour union in the taxi industry, this can result in falling wages for taxi drivers. But in countries such as Indonesia, the strong presence of a labour union has prevented taxi wages from dropping, even with Uber. A large number of app-based rides in such countries can instead create secondary industries or help in shifting informal workers to the formal sector.

However, bearing in mind that there are currently driverless cars being tested in different parts of the world, it is possible that automation can do away with the occupation of driving itself in the future.

Similarly, jobs in logistics are also being increasingly automated. Consider the example of Amazon – given the high degree of automation in its warehouses, Amazon now requires workers with less experience, willing to work for lower wages (The Economist, 2018).

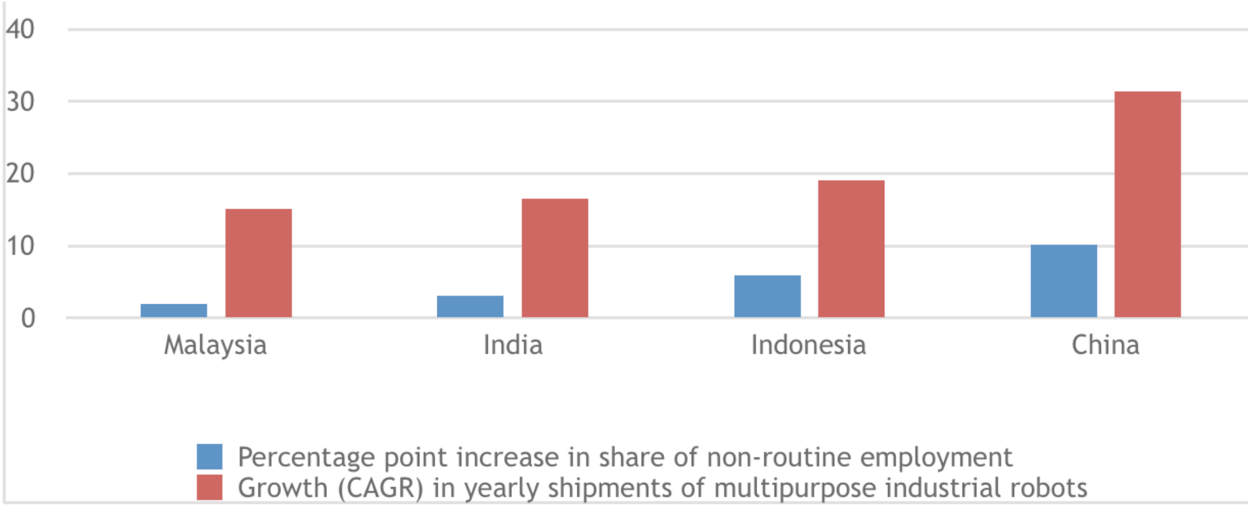
Evidence of routinisation leading to job polarisation is mainly documented for developed economies such as the US, Japan and 16 European economies (see Spitz-Oener 2006; Autor and Dorn 2013; Michaels et al. 2014; Goos et al. 2014; Ikenaga and Kamibayashi 2016). The degree of dislocation of middle-skilled workers varyies significantly. For instance, Goos et al. (2014) estimate that, between 1993 and 2006, the share of middle-skilled jobs remained unchanged in Portugal, but fell by about 5 pp in the Netherlands, and 15 pp in Austria. Although a number of factors can explain the structural shifts in employment – for instance, the degree of technological progress and globalisation, changes in product demand, institutional differences between countries possibly affecting relative wages – the authors find the single most important factor to be routinisation, as described in Autor et al. (2003).

Much less is known about job polarisation in the context of developing economies. Recently, using Autor's (2014) classification, the World Development Report (WDR) (World Bank 2016) finds that the labour markets in developing countries are also 'hollowing-out' – that is, there are declining shares of middle-skilled workers. 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 inter-personal skills such as legislators, technicians and professionals, while low-skilled occupations are intensive in non-routine manual skills such as sales and service workers. WDR (World Bank 2016) finds that, while in the period 1995 to 2012, the average decline in the share of routine employment in developing countries has been 0.39 percentage points (pp) a year, or 7.8 pp over the period, the rate of job polarisation has been lower in developing countries as compared to developed countries (at 0.59 pp a year). Reijnders and De Vries's (2017) study lends further support to the polarisation trend in developing economies. More recently, African Development Bank (AfDB) et al. (2018) find that, between 2005 and 2015, the share of jobs intensive in non-routine[4] tasks in Asian economies has been on the rise – there was a 6.9 pp increase – while routine intensive jobs declined.

Figure 4 takes the case of four Asian countries and examines whether countries with higher robot deployment (a proxy for digitalisation) experience higher increases in the share of non-routine employment. It is observed that the growth in robot deployment in the period 2005–2015 has been the highest in China. This may, in part, explain why China ranks ahead of the other countries in terms of an increase in the share of non-routine employment. The next highest growth in robot deployment is in Indonesia, followed by India and Malaysia. The same ranking is observed in the case of increases in non-routine employment.

[4] Classification into routine and non-routine is based on Autor and Dorn (2013) and excludes agricultural occupations.

Figure 4: Growth in robot deployment and changing nature of jobs (in %)



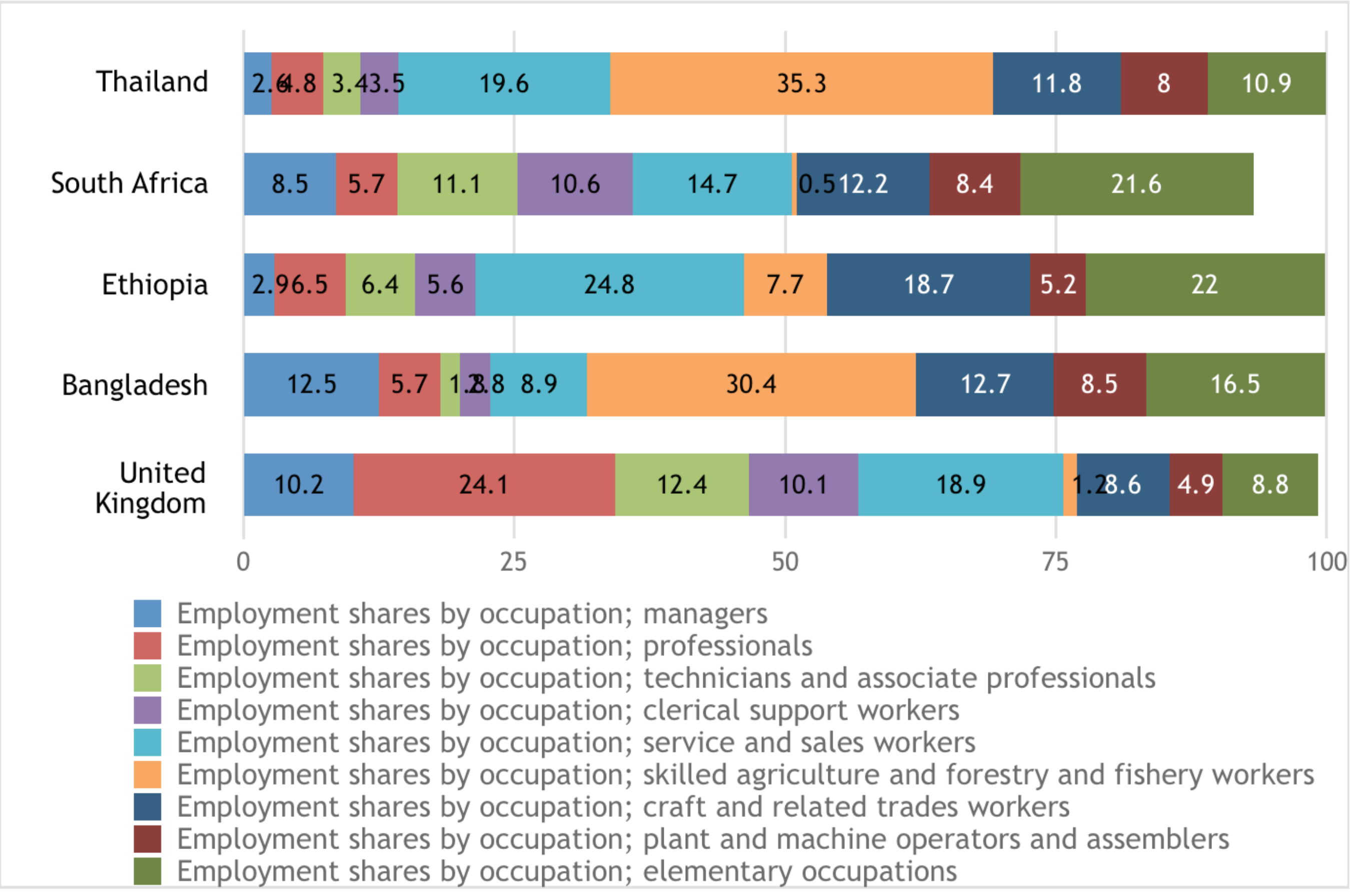
Source: constructed from AfDB et al. (2018) and IFR (2017)

While there is some evidence of polarisation in developing economies, the rate of polarisation has not been uniform across developing economies. There has been job polarisation in Chile in the 2000s (Messina et al., 2016) and in Brazil and Mexico (Maloney and Molina, 2016). In contrast, Almeida et al. (2017) find evidence of digital technologies shifting employment away from skilled workers in Chilean manufacturing in the period 2007–2013, creating more employment in routine and manual tasks. Examining polarisation roughly over the period 1995–2012, WDR (World Bank 2016) finds that, in the case of China, mechanisation of agriculture has led to a rise in routine employment. Ethiopia too, with its large share of manual employment, did not experience job polarisation. In some countries of Latin America, factors such as the commodity boom have played a larger role in shaping the labour market and have benefited the low-skilled workers more than workers in other skill categories. In the case of Argentina, the adoption of ICT in manufacturing between 2010–2012 increased employment levels across all skills categories, with the effect being largest for skilled workers (Brambilla and Tortarolo, 2018).

Das and Hilgenstock (2018) argue that studies which consider broad groups of middle-skilled occupations as routine-intensive tend to overestimate the decline in middle-skilled occupations. The authors point out that, even within occupations, there is heterogeneity in the routine intensity of tasks, not accounted for in the estimates of WDR (World Bank 2016) and Reijnders and De Vries (2017). Das and Hilgenstock (2018) further argue that, for routinisation to result in polarisation, a significant share of the economy must be engaged in middle-skilled occupations. This is not the case in developing economies, where jobs tend to be more concentrated in industries with low susceptibility to automation (International Labour Organization (ILO), 2014; Maloney and Molina, 2016). For instance, roughly 40% of the developing country workforce is employed in the primary sector (ILO, 2014).

Figure 5 confirms that workers in low-skilled occupations (elementary occupations, service and sales) and low-routine occupations (skilled agriculture, forestry and fishery) have the highest employment share in developing countries of Thailand, Bangladesh, South Africa and Ethiopia. In these economies, the employment share of high-skilled workers (managers, professionals, technicians) is below 20%, while the employment share of middle-skilled workers (clerks, crafts and related workers and plant and machinery operators) ranges from 23% to 31%. In comparison, in the developed economy of UK, high-skilled workers have the highest employment share.

Figure 5: Employment shares of occupations across selected economies (in %)



Source: TiVA database (2016). Data for 2013.

Furthermore, one of the factors that can cause routinisation to result in polarisation is a decline in the relative price of investment goods (Das and Hilgenstock, 2018), which is noted to be more of a developed country phenomenon (Dao et al. 2017). While the relative price of investment has declined by about 15% in developed economies between 1990 and 2015, in developing countries it has risen by 13%, as per Das and Hilgenstock (2018). Furthermore, the scope for labour displacement in developing economies is restricted given the low elasticity of factor substitution (Dao et al. 2017).

Although it might take longer compared to developed economies, the relative price of investment goods is eventually likely to fall in developing economies as well due to continuous and significant advances in technical feasibility of digital technologies and falling capital costs. Banga and Velde (2018) 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 reshoring of furniture manufacturing tasks to the US[5] around this time.

Das and Hilgenstock (2018) show that, although the average exposure to routinisation is lower in developing countries – probably due to higher employment in low-routine tasks such as agriculture, fishing and forestry – the exposure to routinisation in developing economies is increasing over time. In the presence of labour market frictions, this means that displaced middle-skilled individuals in developing economies are unlikely to find employment; they do not have the skills to move into high-skilled jobs, while labour market frictions and wage rigidity restrict their movement into low-skilled jobs.

Discussion in this section of the report has highlighted that countries can experience a change in the structure of employment, with varying degrees, as a result of a number of contributing factors: globalisation, digitalisation, changes in product demand and institutional differences. However, evidence of polarisation is mainly concentrated in developed economies and points towards routinisation as the primary reason for 'hollowing-out' of the middle-skilled jobs. While fewer studies have examined polarisation in developing economies, the studies that do exist suggest that polarisation has affected developing economies less than developed economies, at least so far. This may be due to a slower decline in relative prices of investment as compared to developed countries or a larger share of the developing country population being engaged in low-skilled, low-routine occupations. Nevertheless, rising technical feasibility and declining costs of capital globally can increase the potential of digitalisation to impact on the employment structure in developing economies. The promising sectors and occupations for future job growth in developing economies are further explored in Section 4.

[5] 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 analysis does not include other factors such as transportation and time to market costs.

4. What sectors and occupations will attract jobs in the future?

The impact of the digital economy on employment will not only vary across countries, but also across sub-regions and sectors, depending on the rate of automation and the type of technology deployed.

A key finding in Das and Hilgenstock (2018) is that exposure to routinisation varies significantly across industries in developing economies. Agricultural occupations such as skilled agriculture, forestry and fishery workers are the least intensive in routine tasks. It is, however, worth noting that digital technologies have started to enter the low-routine tasks in agriculture as well, increasingly exposing such tasks to automation. For instance, labour shortages in harvesting have given way to the development of "robotic strawberry-picking" (Peters, 2017). Being piloted in Belgium by the company Octinion, this strawberry-picking robot uses machine vision to locate ripe berries, reaches up with a 3D-printed hand to gently pluck each berry and places it in a basket. If it feels that a berry isn't ready for harvest, the robot estimates the date it will be ready and returns to pick it. The Cambridge-based Dogtooth robot can also pick traditional varieties from a British field.

Similarly, services sectors such as accommodation, retail and sales are also less exposed to routinisation – tasks such as sales require inter-personal and communication skills, which are harder to automate (Section 4.1). In contrast, many manufacturing tasks can be automated at a faster rate (Section 4.2).

4.1 Future of jobs in the services sector

As per the World Economic Forum (WEF) Job Survey report (2016), which covers nine sectors in major developed and emerging countries,[6] technology is expected to increase overall employment by 2% in the period 2015–2020, with increase in the *services sectors* of computer and mathematical, sales and related, architecture and engineering, management, business and financial operations, driven by technologies such as mobile internet, cloud computing, Internet of Things (IoT), big data and robotics.

A recent survey by Capgemini[7] (2017) in the US, UK, 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 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

[6] This survey sample covers nine sectors (financial services and investors; ITC; energy; basic services and infrastructure; mobility; consumer; healthcare; media, entertainment and information; and professional services) in 13 major developed and emerging economies (Australia, Brazil, China, France, Germany, India, Italy, Japan, Mexico, South Africa, Turkey, UK, US) and two broader regional groupings – Association of Southeast Asian Nations (ASEAN) – combining results for Indonesia, Malaysia, Singapore, Thailand – and the Gulf Cooperation Council (GCC) – combining results for Kuwait, Qatar, Saudi Arabia, and the United Arab Emirates.

[7] A Paris-based multinational information technology consulting corporation.

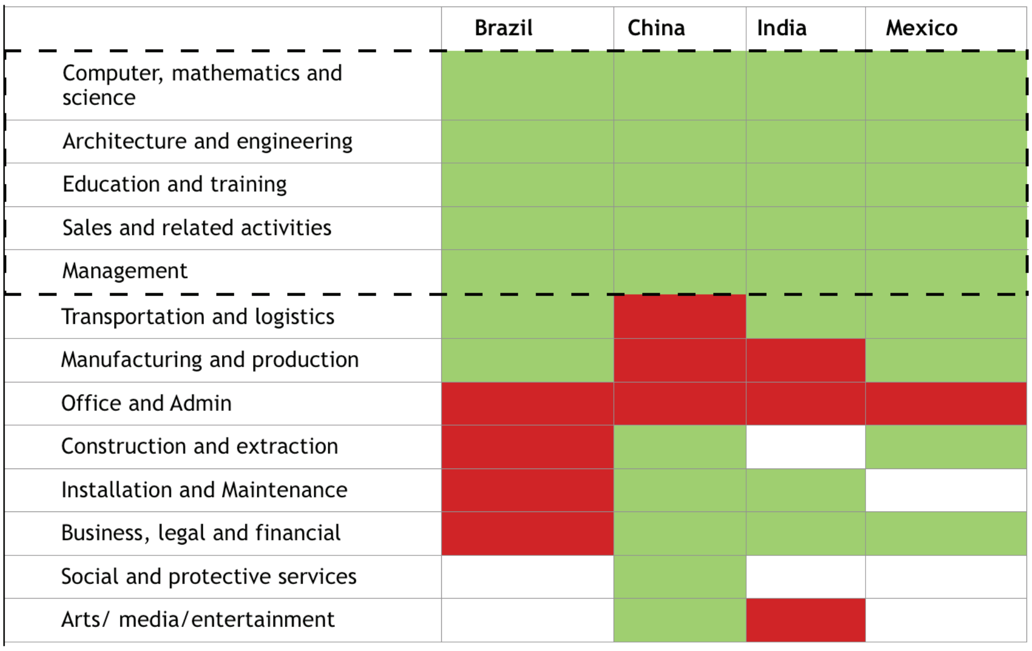
across the entire production chain, indicating the increasingly important role of ICT services in the manufacturing processes. This also highlights the growing role of data processing services and the need for advanced data analytics.

However, in some services sectors, certain 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 of the secretarial services, including office tasks such as calendar management, documents and filing support, as well as technical services such as social media support, email marketing, transcription, and so on.

Tasks in financial services, such as data entry, 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.

Table 1 shows that, for developing economies of Brazil, China, India, and Mexico the **'mainstay'** sectors – that is, sectors that are going to become or remain important in the future (as a result of growth or stability in employment) include service sectors of computer, mathematics and science, architecture and engineering, education and training, sales and related activities, and management. In contrast, employment outlook is negative for the office and administrative sector across all developing economies. Manufacturing and production is expected to experience a decline in employment in China and India, with transportation and logistics being a 'sceptic' sector for China, which is ahead on the technology frontier compared to the developing economies considered.

Table 1: Employment outlook 2020



Key: Green boxes denote growth in employment or stable employment by 2020, and red boxes denote decline in employment
Source: constructed from data in WEF jobs survey report (2016)

4.2 Future of jobs in the manufacturing sector

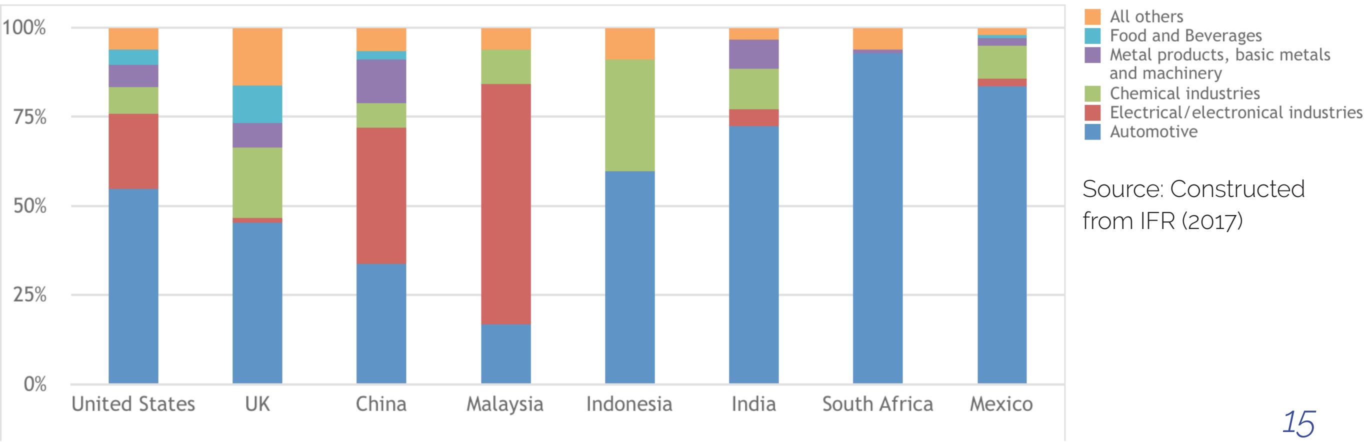
For manufacturing and production, the WEF Job Survey (2016) predicts an overall decline of 1.6% in employment across developed and developing countries in the period 2015–2020, largely driven by labour-substituting technologies, such as 3D printing, which is expected to reduce employment by 3.5%. However, caution is warranted here, since these estimates do not account for an increased manufacturing demand for advanced materials and the potential for labour-complementing productivity improvements through digital technologies such as robotics.

Even within the manufacturing sector, the rate of automation depends on technological and economic feasibility, implying that industries are being automated at different rates. For instance, compared to the automotive sector, robots in the garments sector need to have a lot more dexterity, for example, for tasks such as stitching and embroidery. At the same time, average wages in the garments sector are relatively lower compared the automotive sector, indicating that automation may not be economical as yet.

Figure 6 compares the distribution of robot sales across the main industries of selected countries. It is observed that robot deployment in the US, UK and China is much more diversified – that is, robots are being used in all of the following industries: automotive, electrical, chemical, metal products, food and beverage and 'other' (which includes apparel, 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/electronic industries. 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).

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 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 in developing countries may be overstated.

Figure 6: Distribution of robots across different industries



Source: Constructed from IFR (2017)

5. The changing demand for skills in the digital economy

While digital technologies will make some jobs redundant, they are more likely to affect overall jobs, through substituting specific tasks in a job. This will free up workers to perform other tasks or new tasks that will require new skills.

To identify the skills that will potentially become important in the future, this section first develops a Skills-Tasks matrix to help 'unpack' the skills needed in different types of tasks (Section 5.1). It then examines the changing occupational structure and associated skills needed in developing countries (Section 5.2). Building on this, Section 5.3 identifies the future skills needed in a digital economy. It uses concepts of 'core skills' that directly increase the competitiveness of workforce in the digital economy and 'ancillary' skills that are more difficult to automate – and therefore remain relevant in the digital economy, or support the digital economy but do not directly contribute to it. Within core skills, the study distinguishes between digital skills and soft skills and conceptualises the interaction between the two. This is presented as the 'digital economy skills nexus'.

5.1 Developing a Skills-Tasks matrix

The impact of digitalisation will depend on the type of task being performed by workers. Autor et al. (2013) distinguish between routine and non-routine tasks. Goos and Manning (2007) and Spitz-Oener (2006) follow this by classifying tasks into five categories: routine cognitive (eg record-keeping, repetitive customer service); routine manual (eg repetitive assembly); non-routine cognitive (eg legal writing); non-routine manual (eg truck driving); and non-routine interactive (eg managing and supervising). Autor and Dorn (2013), on the other hand, distinguish between three types of tasks: abstract tasks (eg problem-solving and managerial tasks); routine tasks; and manual tasks.

Drawing on these studies, Figure 7 presents a Skills-Tasks matrix as a first step in understanding the different skills that will be in demand in the digital era, based on the type of task being performed. The matrix distinguishes between four types of tasks, routine versus non-routine tasks (given in the rows of the matrix), and manual tasks versus cognitive tasks (given in the columns).

Routine tasks refer to those that follow explicit rules and can therefore be more clearly codified. Automation and robots are more likely to substitute such tasks than non-routine tasks, which do not follow a set pattern of rules and require more tacit knowledge and interactions with people. Non-routine tasks of designing, creating art, conducting research, managing and supervising teams, nursing, child care, and cleaning have proven hard to automate.

Manual tasks refer to physical tasks performed by labourers or service occupations that need low skills but are harder to automate (Acemoglu and Autor, 2011). On the other hand, cognitive tasks are often 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. Robots and other ICT capital are often complementary to workers performing cognitive tasks – they can increase productivity for workers who possess analytical and inter-personal skills, or even manual skills that require dexterity (Acemoglu and Autor, 2011).

Using different combinations, four types of task categories, and associated skill categories, emerge: routine-manual tasks, routine-cognitive tasks, non-routine manual tasks, and non-routine cognitive tasks.

Routine-manual tasks such as operating machinery, carpentry and constructions are more likely to be performed by middle-skilled workers with physical skills. In such tasks, not much analytical thinking is needed once the skill is learnt; tasks are repetitive in nature and are therefore being increasingly automated across developed and developing countries. This is in line with results from Table 1 which show a declining employment outlook in Brazil for construction and extraction industries, which are more intensive in routine-manual tasks. Even in some African economies, such tasks are now being automated – see Banga and Velde (2018) for a case study on the Kenyan furniture manufacturing firm FunKidz that is using computer numerical control technology to cut and shape children's furniture.

However, when examining the potential of such tasks being automated, it is important to consider the dimension of technical feasibility. Some routine manual tasks require hand dexterity, such as stitching in garments, as yet not easily done by robots. Although there are few examples demonstrating the potential of upcoming technologies in these tasks – see for instance, Banga and Velde (2018) for a case study on the A-Z Textile Mill in Tanzania and how modern cutting lasers are replacing workers in the garments sector – digital technologies have not yet fully diffused in such tasks on a wide scale, due to technological and economic infeasibility.

Routine-cognitive tasks, also performed mostly by middle-skilled workers, are associated with jobs of book-keepers, secretaries, bank tellers and clerks. These routine tasks are also being automated at a fast rate – for instance, a large number of stores already have self-checkout counters instead of cashiers, and free business management software such as Money Manager EX, TurboCASH, and so on.

Non-routine manual tasks involve agile physical skills (for instance, required in truck driving or operating vehicles) as well as 'soft' skills (skills that are harder to measure) such as interpersonal skills for sales occupations, and socio-emotional or empathetic skills (for service occupations such as nursing, caring, janitorial work, security work etc). Such tasks are harder to automate and generally performed by low-skilled workers.

Non-routine cognitive tasks require job-neutral 'hard' skills (measurable skills) such as digital skills (for collecting online information, data analysis, etc), job-neutral 'soft' skills, such as interpersonal skills, managerial skills, analytical thinking and creative-thinking skills. They also involve job-specific skills – for instance, legal writing, coding and programming, health-care, education and training, professional and technical services.

Figure 7: Skills-Tasks matrix

	Manual	**Cognitive**
Routine	**Physical skills** such as controlling and operating machinery, assembling parts, construction, carpentry.	**Enterprise skills** such as book-keeping, accountancy, pay-roll processing, cashier and clerk work
Non-routine	**Physical skills** of operating vehicles, industrial truck operations, **Interpersonal skills** and **socio-emotional and empathetic skills** for sales occupations and service occupations such as security work, caring, janitorial services.	**Job-neutral** hard skills such as basic and intermediate digital skills, proficiency in foreign language. **Job-neutral** soft skills such as interpersonal skills, managerial skills, analytical and critical thinking, problem-solving and creative and design skills. **Job-specific** hard skills such as legal skills, pharmacy skills, advanced digital skills

Source: Authors (2018)

5.2 Changing occupational structure and skills needs in developing countries

Figure 7 highlighted the skills associated with different task categories. This section examines how the occupational structure is changing in developing economies, in the context of the digital economy, and the associated skills needs. It identifies the task categories that are going to attract future job growth in the digital economy.

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 to 15%, from a current level of 11%. Similarly, there are going to be changes in skills requirement within a job. For instance, among all the jobs requiring cognitive abilities as part of their core skill sets, 52% of the jobs do not have such requirements now and are expected to have increasing demand of cognitive abilities by 2020 (WEF job survey report, 2016). As per the report, cognitive abilities, system skills (evaluation and analysis of systems) and complex problem-solving skills are expected to be the top three skills demanded in the future.

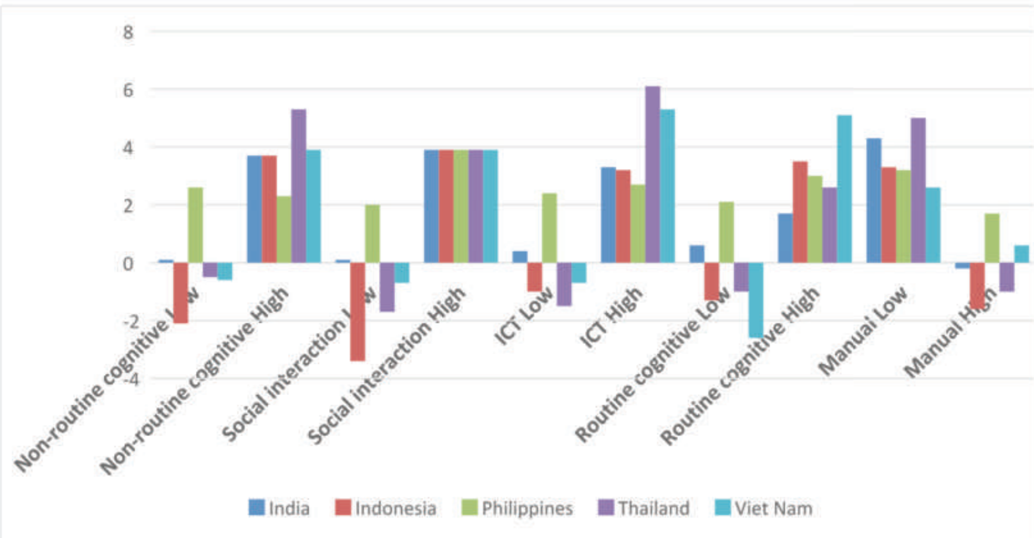
The rise in demand for workers performing non-routine tasks has also been an increasing trend in a number of economies. Since the 2000s, the employment share of occupations intensive in non-routine cognitive skills (such as analytical and critical thinking) and socio-emotional skills has increased from 19% to 23% in emerging economies, and from 33% to 41% in advanced economies (WDR, World Bank 2018 working draft). Across countries, higher-order cognitive skills, such as technical skills, and socio-emotional skills are consistently ranked as top valued skills by employers. Employers in Benin, Liberia, Malawi and Zambia suggest that technical skills, teamwork, communication, and problem-solving skills are the most important sets of skills for the future (Arias et al. forthcoming, as cited in WDR, World Bank 2019 working draft). In middle-income countries in Europe, such as in Bulgaria and

Romania, the demand for non-routine cognitive and interpersonal work is increasing, but there is no increase in demand of low-skilled non-routine manual work (Gorka et al. 2017). Similarly, cognitive work has increased in other countries such as Botswana, Ethiopia, Mongolia, the Philippines, and Vietnam (see Mason et al. 2018 and World Bank, 2016).

Asian Development Bank's (2018) analysis of employment trends in five developing Asian economies (India, Indonesia, the Philippines, Thailand, and Vietnam) over the past decade confirms that jobs with a high frequency of interactive tasks (such as negotiations or group activities), cognitive tasks (such as writing memos, analysing data, and preparing charts and tables), and/or using ICT to perform complex tasks, have experienced relatively higher growth in employment and wages (see Figure 8). For example, employment in these types of jobs in the mentioned Asian countries expanded 2.6 pp faster than total employment annually (ADB 2018). In contrast, jobs intensive in manual work, which are already low paid, have experienced limited employment and wage growth, contributing to rising inequality.

Detailed analysis of occupation titles in three Asian countries – Malaysia, Philippines and India[8] – by the ADB (2018) further reveals that new types of jobs have emerged to handle new technologies. Occupations with the highest proportion of new job titles in the three Asian economies include: 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; database and network professionals; and other health-related professionals. In India, a significant share of new job titles has also emerged in the middle-skilled occupations in craft and related trades – the fastest growing occupation category in the country. The creation of new job titles in these occupations is possibly driven by the different types of technicians needed to work with computer numerical control machines (ADB, 2018).

Figure 8: Annual employment growth (in %) in jobs, by task-intensity and type.



Source: reproduced from ADO (2018).
Note: The time frames vary across countries; Vietnam (2007–2015), Thailand (2000–2010), India (2000–2012), the Philippines (2001–2013), and Indonesia (2000–2014). Jobs are classified in terms of whether they are high-intensive or low-intensive with respect to the five task categories.

[8] Data is for: Malaysia 2008; India 2015; Philippines 2012.

5.3 Skills needs of the future

Section 5.2 has highlighted non-routine cognitive tasks as the most promising task category in the future. In the increasingly digital economy, higher job growth is expected in non-routine cognitive tasks, compared to other types of tasks. Consequently, skills based on tacit knowledge and interactions between people – for example, teamwork, management and care-giving – will be in higher demand. A rapidly evolving world of work will also require adaptability and flexibility from workers, which will enable them to shift easily from one job to another (WDR, World Bank 2019 working draft). This suggests the increasing importance of a 'skill-set' of cognitive skills (such as critical thinking and problem-solving), interpersonal skills, managerial skills and creative skills.

Drawing on both the Skills-Tasks matrix (Section 5.1) and the changing occupational and skill structure (Section 5.2), Figure 9 maps out the future skills needs. These skills refer to those needed to perform non-routine tasks, and can be classified into 'core' or 'ancillary' skills to the digital economy.

Core skills are those that directly contribute to increasing competitiveness of workers in the digital economy and include: a) job-neutral basic to intermediate digital hard skills; b) job-specific digital skills which refer to specialist digital skills; and c) job-neutral soft skills such as interpersonal skills, managerial skills, analytical, critical thinking and problem-solving skills as well as creative skills and adaptive skills.

In comparison to 'core' skills, 'ancillary' skills are those that remain relevant in the digital economy (such as job-specific legal and pharmacy skills) or that support the digital economy but do not directly contribute to it, such as: a) socio-emotional and empathetic skills needed for low-skilled service occupations of child-care and nursing; and b) physical skills – for instance, operating industrial trucks and other vehicles. In some cases, digitalisation can create employment for such skills. For example, a rapid rise in e-commerce is likely to create service jobs, such as inventory and parcel delivery, which will require more industrial drivers in the short-run but can possibly be performed by autonomous cars in the long-run. On the other hand, as per WDR (World Bank 2019, working draft), the demand for narrow, job-specific skills is falling.

Figure 9: Core and Ancillary skills in the digital economy

Core skills in the digital economy

Job-neutral digital skills – basic to intermediate: eg data analysis
Job-specific specialist digital skills – eg computer programming
Job-neutral cognitive skills – eg analytical and critical thinking, problem-solving, creativity
Job-neutral interpersonal skills – eg communication, collaboration, management

Ancillary skills in the digital economy

Interpersonal skills – eg communication for sales occupations
Socio-emotional skills for low-skilled service occupations – eg empathy for nursing
Physical skills that require dexterity – eg truck driving
Job-specific hard skills – eg legal writing

Source: Authors (2018)

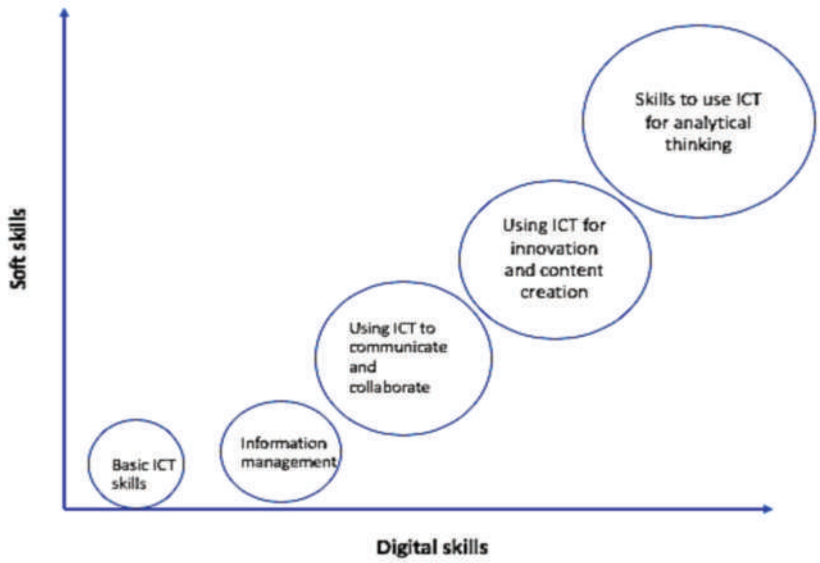
Under core skills, *basic digital skills* are industry-neutral skills needed for using the internet, mobile phones, browsing the web, sending emails, and so on. These skills are important for workers to function at a minimum level in a digital economy. Basic digital skills can be further broken down into basic hardware skills – the skills to operate a computer and touch-screen smartphones, as well as basic software/online skills such as emailing and searching the internet which can help gain access to information and people (ITU, 2018).

Intermediate digital skills refer to skills for engaging with internet and digital technologies in a more productive manner. This includes 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 internet to carry out such tasks (that is, cybersecurity). These skills prepare workers for a wide range of digital tasks and help them adapt as technology changes. For instance, data skills feature more prominently as the data revolution gains further momentum, generating demand for skills needed to produce, analyse, interpret, and visualise large amounts of data (ITU, 2018).

The third category – *specialist digital skills* – are job-specific and crucial to the digital economy. These include special 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). These skills are associated with jobs in sectors of computer, science and mathematics and architecture and engineering that have been previously identified as the 'mainstay' industry sectors.

Combining digital skills with soft skills such as communication, management and analytical thinking, Figure 10 presents a two-dimensional nexus for 'core' skills in the digital economy. Soft skills are represented on the Y axis and digital skills on X axis, with the width of the circles representing the importance of the skill to the digital economy – that is, the bigger the circle, the more relevant the skill is to the digital economy.

Figure 10: The digital economy core skills nexus



Source: Authors (2018), compiled from Laar et al. (2017) and ITU (2018)

The smallest circle represents basic ICT skills – that is, ICT knowledge and use of hardware and software necessary to function and operate in a digital economy. The next-largest circle refers to information management that requires intermediate digital skills needed to use ICT to effectively search, organise and use electronic information. This will require judging the usefulness of the acquired information and the ability to coherently collate and analyse information and data from different sources (Laar et al., 2017).

There are jobs that require intermediate digital skills as well as communication skills – for example, using ICT to communicate information effectively through social media and online platform (such as digital marketing), and managing and collaborating by digitally exchanging information or sharing ideas on online platforms (for example using online project management software such as Trello and Zoho). Similarly, using ICT to create new content and knowledge requires intermediate to specialist digital skills and soft skills of creative and innovative thinking (for instance, advanced technology design).

The largest circle represents skills for using ICT for making informed decisions, negotiating, understanding and solving problems in a digital context. This involves specialist digital skills as well as soft skills. For instance, the digital technology of 3D printing involves the knowledge of computer-aided design and 'additive manufacturing' which requires advanced digital skills of 3D modelling as well as soft skills of problem-solving, critical thinking and creative designing. Another example would be systems engineering which requires computer engineering skills along with leadership, project management and communication skills.

6. Assessing skills-readiness in the digital economy

Several studies find evidence for the persistence of a digital divide in access and use of digital technologies (see for instance, Banga and Te Velde, 2018). Over the past few years, emphasis on the divide has shifted to include skills that are necessary to effectively use digital technologies and the internet. This has been referred to in the literature as the "second-level divide" (Hargittai 2002), which differs across regions. The Human Capital Index by the WEF (2017) ranks 130 countries in terms of how well they are developing their human capital across four areas: capacity, deployment, development and know-how. At the regional level, the human capital development gap is found to be the smallest in North America and Western Europe, and largest in South Asia and Sub-Saharan Africa. But even within regions, there are differences in the overall human capital outcomes across countries.

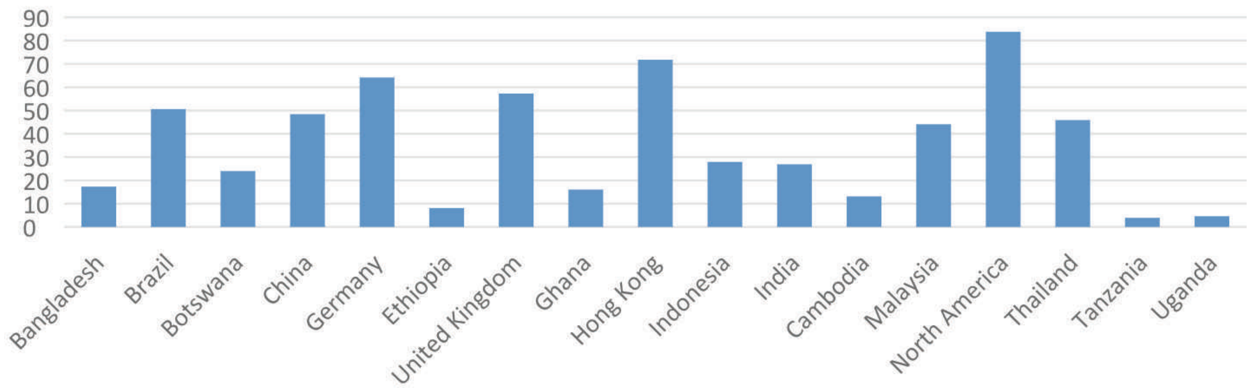
This section compares the skills-readiness of countries for competing in the digital economy based on tertiary and vocational education (section 6.1), how countries are faring in the Skills-Tasks matrix (section 6.2) and skills shortages (section 6.3). Selection of indicators and countries is guided by data availability.

6.1 Assessing skills-development based on education

Education plays an important role in addressing the different skills needs in a digital economy. For instance, skills developed through tertiary education and higher education, such as engineering and architecture, are important, along with skills developed through vocational education. Development of a curriculum that teaches basic literacy and technical skills and also teaches soft skills that can prepare the future workforce of countries is essential.

Figure 11 assesses skills development in countries using the tertiary education enrolment ratio. North America, Germany and the UK have a significantly higher share of tertiary enrolment in gross enrolment – 83%, 64% and 57% respectively. Among the developing economies considered, only Hong Kong has enrolment rates comparable to the developed countries. Other developing economies, particularly African countries, are lagging.

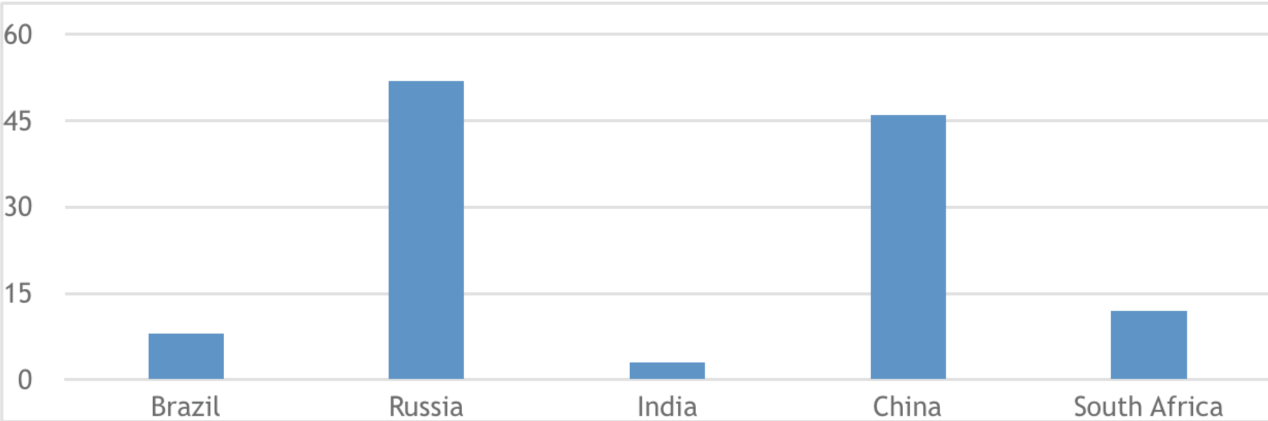
Figure 11: Tertiary enrolment, as a percentage of gross enrolment



Source: World Development Indicators (WDI) Note: Data for countries is for 2016, except Brazil, Germany, UK, Cambodia, Thailand and Tanzania (2015). Data for Ethiopia and Uganda is for 2014. Gross enrolment ratio for tertiary school is calculated by dividing the number of students enrolled in tertiary education (regardless of age) by the population of the age group that officially corresponds to tertiary education.

Differences are also evident in the case of vocational education, introduced in most of the countries (including BRICS nations – Brazil, Russia, India and China) at the upper secondary level (BRICS business council, 2016). Among the BRICS countries, Russia and China have much higher participation in vocational education – 52% and 46% respectively (see figure 12) – comparable to France and Germany which have an enrolment rate of around 45% in vocational courses at upper-secondary level.

Figure 12: Percentage of students enrolled in vocational courses in BRICS



Source: UNECSO statistics

6.2 Assessing skills-development using the Skills-Tasks matrix

Examining routine tasks (as specified in the Skills-Tasks matrix in Figure 7), Figure 13 shows that US scores higher in routine cognitive skills compared to developing economies. By contrast, African economies of Rwanda and Tanzania score higher in routine manual skills. In terms of soft skills and non-routine manual skills, the US ranks higher in both analytical and inter-personal skills, with African economies of Rwanda and Tanzania having the lowest score on these soft skills (Figure 14). On the other hand, African economies score higher on non-routine manual physical classified under 'ancillary' skills in Figure 9.

Figure 13: Score on routine skills[9]

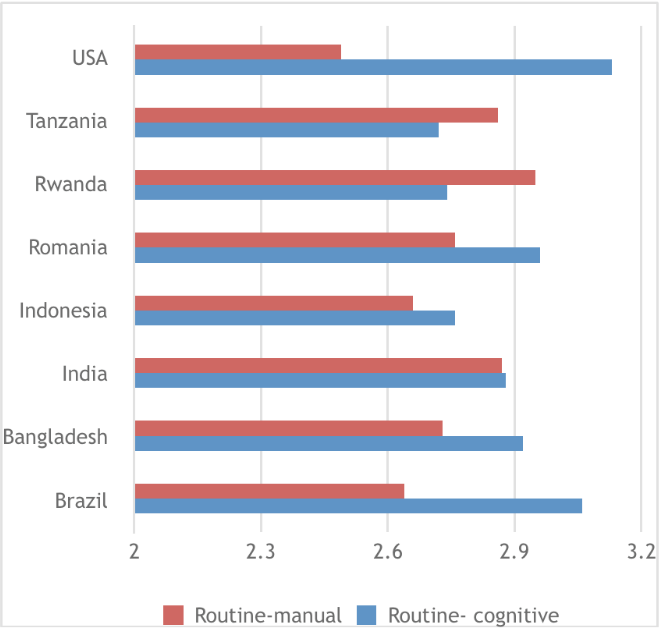
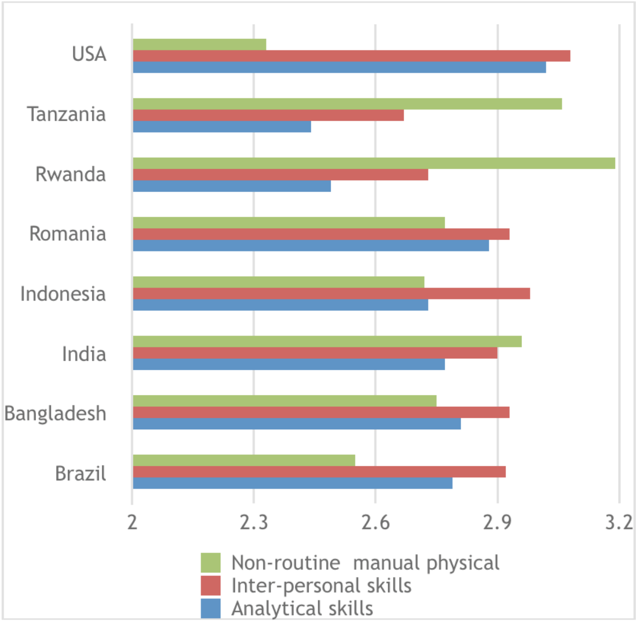


Figure 14: Score on Soft and periphery skills[10]



Source: Data are from Aedo et al. (2013).

Note: Aedo et al. (2013) combine data on skills content per occupation, using the Occupational Information Network (O*NET) with the labour force structure to provide occupation-based skill-measurement scores for 30 countries. Scores are based on routine skills, non-routine manual skills, inter-personal skills and analytical skills

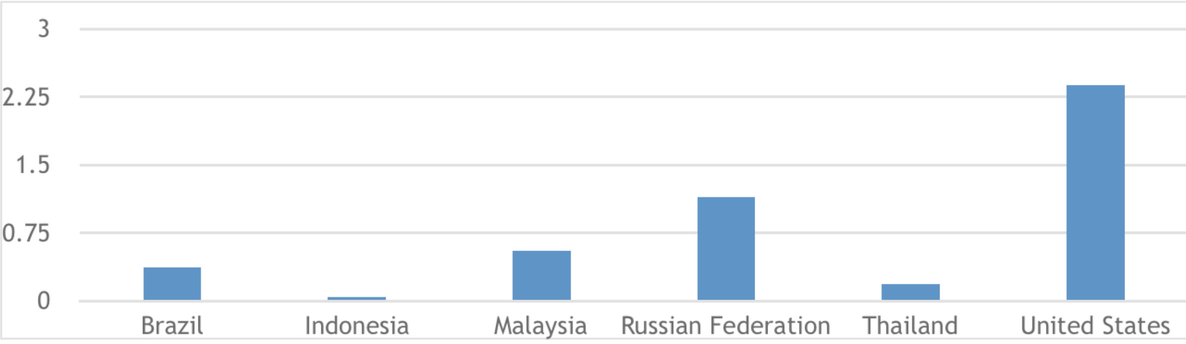
In terms of digital skills (classified as core skills in Figure 9) analysis of the ITU survey database for 2014–2016 reveals that most adults in low- and middle- income countries do not perform even the most basic ICT functions, with only 4% of adults in Sudan and Zimbabwe being able to copy and paste files; and only 2% to 4% in Egypt, Iran, Jamaica and Pakistan being able to use basic arithmetic formulas in a spreadsheet (UNESCO, 2017).

As for digital specialist skills, it is observed 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. Figure 15 shows that 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.

9 Routine manual skills use information ability to adapt to the speed of the equipment, to control machines and processes, and time spent time making repetitive motions. Routine cognitive skills are based on the ability to repeat the same task, to be exact and to handle structured work (Aedo et al. 2013).

10 Non-routine manual skills are based on the ability to operate mechanised devices and vehicles, handle objects, dexterity and spatial orientation. Analytical skills measure is based on the ability to analyse data/information, to think creatively and to interpret information, while the interpersonal skills measure uses information on the ability to maintain personal relationships and manage others (Aedo et al. 2013).

Figure 15: ICT professionals in total employment (in %)

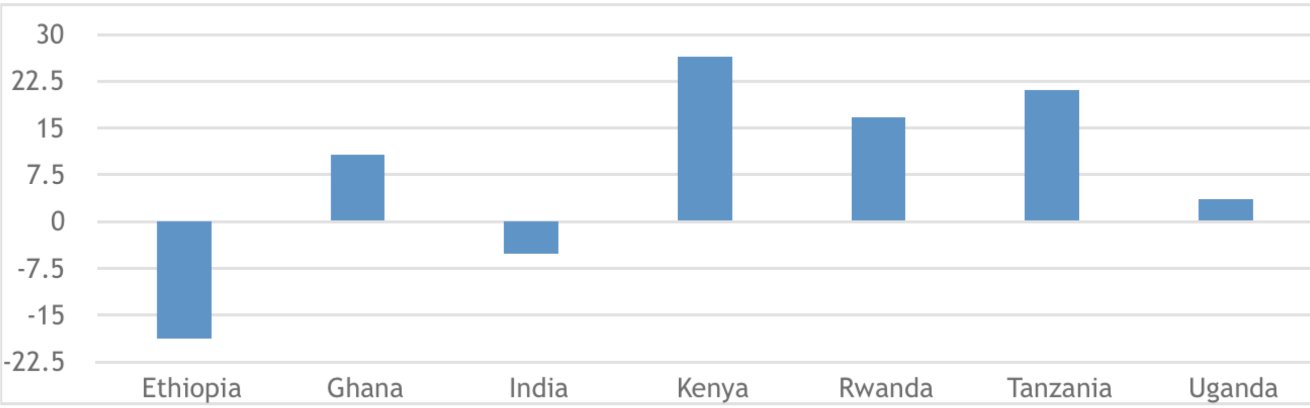


Source: ILOSTAT. Data is for 2016.

6.3 Assessing skills shortages

As mentioned above, some studies argue that digitalisation is likely to lead to displacement of middle-skilled workers in developing economies. While labour market frictions and wage rigidities may restrict middle-skilled workers from moving into lower-skilled jobs, they are also unlikely to find employment in more skilled or new jobs created in the digital economy that need higher skills. This is particularly significant in Latin America (Melguizo and Perea, 2016), and in Africa. In the period 2006–2013, the percentage of firms identifying inadequately skilled workforce as a major constraint to firm operations increased in many African economies; roughly by 26 pp in Kenya, 2 pp in Tanzania, 16 pp in Rwanda, 11 pp in Ghana and 3.6 pp Uganda. The skills gap has fallen in the case of India (5 pp) and Ethiopia (18 pp). See Figure 16.

Figure 16: Percentage point change in skills gap



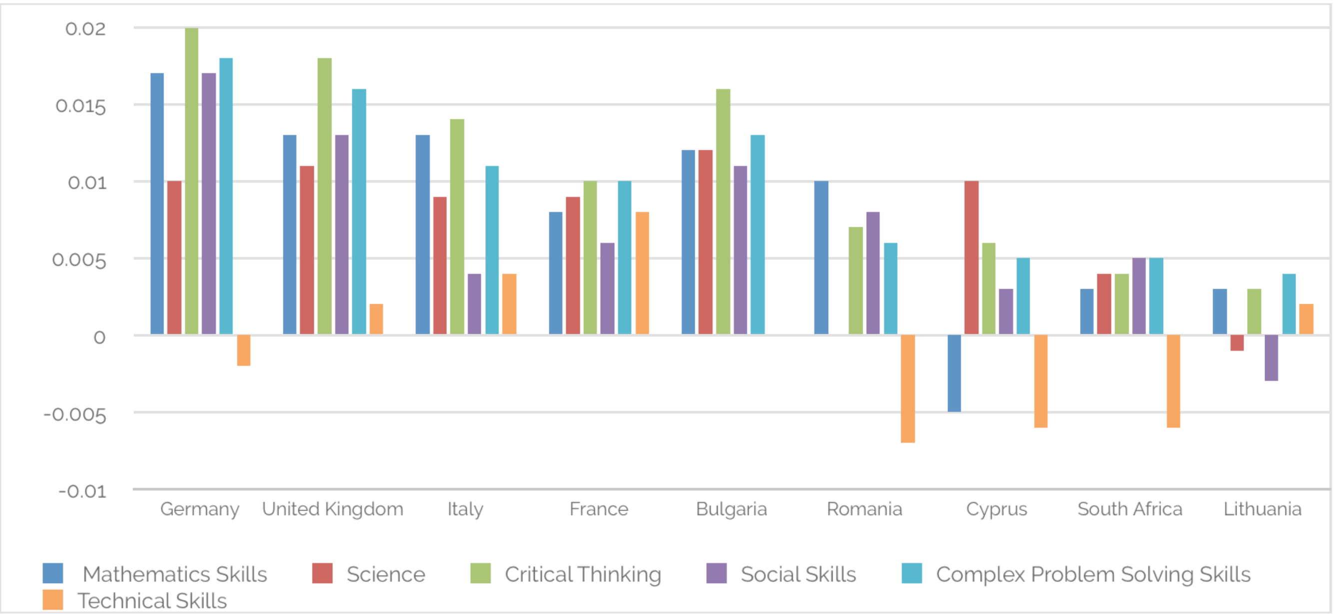
Source: World Business Environment Survey (WBES).

Notes: Skills gap is measured as the percentage of firms reporting an inadequately skilled workforce as a major constraint to firm operations. Data dates are: Ethiopia 2006–2011; Ghana 2007–2013; India 2006–2014; Kenya 2007–2013, Rwanda 2006–2011; Tanzania 2006–2013; Uganda 2006–2013.

To examine which skills are in shortage across developed and developing economies, data sets are obtained from the Trade in Value Added (TiVA) database.[11] Figure 17 shows a skills shortage in developed countries – the UK, Italy and France – in mathematics and science skills, critical thinking and problem-solving skills, social skills and technical skills (operations analysis, technology design, equipment selection, installation, programming, operation monitoring, equipment maintenance, trouble-shooting, repairing, quality-control analysis). Of these countries, only Germany has a surplus in technical skills.

In developing economies of Romania and South Africa, there appears to be an overall surplus of technical skills, but a shortage of problem-solving skills, social skills, critical thinking skills and math and science skills. Data from TiVA reveals that, within technical skills, there is a shortage in skills of *operations analysis and programming* in the two countries, with Romania also having a shortage in technology design. Across Romania and South Africa, there is surplus in technical skills of quality control, troubleshooting, equipment maintenance and installation. However, it is important to note that, with growing digitalisation of economic activities, technical skills such as troubleshooting are also becoming automated through artificial intelligence (WEF, 2016).

Figure 17: Skills shortage across countries by type of skill



Source: TiVA database (2016). Data for 2013.

Note: Mathematical/science skills refer to using mathematics/scientific rules and methods to solve problems. Critical thinking refers to use of logic and reasoning, social skills include interactive and negotiation skills, complex problem-solving skills refer to developed capacities used to solve novel problems in complex, real-world settings. Technical skills include digital skills such as programming and technology design.

[11] TiVA matches occupations to measures of skills requirements for each occupation using the US O*NET database which covers cognitive and non-cognitive skills as well as tasks. The final skills shortage indicator adjusts the different skills requirements for each occupation by the extent of an occupational shortage index.

7. Conclusion

The main objective of this study was to examine the future of skills in developing economies in the context of rapid, global digital progress. Considering that the future of skills differs across regions, countries, sectors and tasks being performed, the study conducted a literature review and undertook data analysis relating to how developing economies are faring in the digital economy, especially with respect to the implications of digitalisation for the level and structure of employment, and the likely sectors and tasks that are going to become important in the future.

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 sectors and occupations are likely to be in demand in the future. In terms of future sectoral job growth in developing countries, it is expected that there will higher employment growth in services sectors such as computer, mathematics and science, architecture and engineering, education and training and sales and related activities and management. In contrast, office and administrative services, financial services, as well as clerical and logistical services, face high exposure to routinisation. Although overall the manufacturing sector faces higher exposure to automation than services, the rate of automation differs across industries, depending on relative wages, dexterity in production and technical feasibility. Impact of robot deployment will also differ across industries – for instance, in developing Asia, robot deployment is concentrated in the more capital-intensive industries which employ relatively fewer people than traditional industries.

Occupations that are intensive in non-routine manual tasks and non-routine cognitive tasks are expected to experience growth in the future. Non-routine manual tasks require dexterous physical skills (such as for driving trucks) as well as socio-emotional skills for nursing and caring. Non-routine cognitive tasks, on the other hand, require more skilled-workers with 'hard' skills such as digital and professional skills as well as 'soft skills' of management, collaboration, communication and analytical thinking.

In the context of the digital economy, the study identifies core skills that can directly increase competitiveness of workforce, and ancillary skills that either remain relevant or support the digital economy, but do not directly contribute to it. Core skills that need to be developed include: a) job-neutral digital skills; b) job-specific digital skills; and c) job-neutral soft skills such as communication, management, analytical and critical thinking and creativity. Ancillary skills that can support the digital economy include: a) physical skills that require dexterity; and b) socio-emotional and interpersonal skills for service and sales occupations.

The skills-readiness of developing economies is lagging compared to the developed economies. Developing economies have a lower share of tertiary and vocational enrolment, and a lower share of ICT professionals in total employment. They rank lower in routine-cognitive, inter-personal and analytical skills, but higher in non-routine manual skills. Skills-shortages have increased over time in some African countries.

To become competitive in the digital economy, developing economies need to adapt to the rapidly changing skills landscape. This paper tries to identify these skills, which need to be acquired and built using targeted policies. How to do this forms an important topic for future research.

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