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Technological change and innovation are key drivers of economic change. *Industry 4.0* is a term given to the current wave of technological change, underpinned by advances in the connectivity between humans and machines. It is the fourth industrial revolution. The term is "applied to a group of rapid transformations in the design, manufacture, operation and service of manufacturing systems and products" (Davies 2015). It originated in Germany and the German Chancellor Angela Merkel defined it as "the comprehensive transformation of the whole sphere of industrial production through the merging of digital technology and the internet with conventional industry" (Davies 2015). For the purposes of this report, Cambridge Econometrics defines Industry 4.0 as the future digitalisation of the economy driven by the latest technological changes in ICT, cyber-physical systems, network communications, simulation, big data and cloud computing, and AI.

There is much speculation about the nature and scale of the potential impacts of Industry 4.0; like previous industrial transitions, Industry 4.0 will have far-reaching implications for the way that we live and work.

This Foundation Report recommends how the NSRD take forward its own research into the potential impacts of Industry 4.0

Cambridge Econometrics (CE) has been commissioned by the British Council to prepare this *Foundation Report* to recommend how the National Skills Research Division (NSRD) should take forward its own research into the potential impacts of Industry 4.0, on the economy, and on current and future skills in India.

Three key questions are answered by this *Foundation Report*:

1. What is the evidence of the impact of Industry 4.0 from international research?
2. What research methodologies have been used to examine the impacts of Industry 4.0?
3. What research methodologies and tools are recommended for further research in India?

The skills landscape in India

The answers to these questions should be interpreted in the context of the labour market landscape in India and the future challenges and opportunities (see Chapter 3).India's labour force is characterised by an increasing supply of young but unskilled workers, with low levels of education, and by low participation rates amongst women. The country's growing workforce is younger than the workforce in other advanced economies, but India is falling behind in developing its skills base.

Industry 4.0 will create new roles requiring additional skilled workers, while existing jobs will be vulnerable to automation. Hence, it is vital to train the labour force to avoid high unemployment and to exploit the opportunities offered by Industry 4.0.

Before the creation of the Ministry for Skill Development and Entrepreneurship (MSDE) in 2014, responsibility for vocational training was spread across 20 ministries, resulting in fragmentation of the training system and duplication of efforts. The training system had not been effective in increasing the quality of the labour force and its employment opportunities.

Only limited literature was found in the public domain from government/public bodies and specific to India

The findings synthesised in this report are drawn from a focused review of international evidence. Only limited literature was found in the public from government/public bodies and specific to India. It is acknowledged that some of the evidence reviewed, e.g. from business media and industry stakeholders, may represent a specific perspective. The nature of the research remains speculative because it is trying to predict the future impacts of new and future (as yet unknown) technologies which have the potential to disrupt the economic system and to bring dramatic changes. Nonetheless, valuable insights have been drawn and some key messages emerge.

What is the evidence of the impact of Industry 4.0 from international research?

Industry 4.0 is likely to accelerate structural changes in the Indian economy (see Chapter 4). One of the most significant impacts of Industry 4.0 is expected to be automation and its consequences for the numbers and types of jobs. Some sectors and occupations are likely to be more impacted than others based on the economic barriers to automation, the education level and skills of their workforce, the nature of the tasks and activities of jobs and how labour intensive the sector is. The pace of automation will depend on the relative costs of robots (including energy inputs, maintenance and repairs) relative to human workers, as well as their relative productivity. In higher-cost western economies, Industry 4.0 is expected to accelerate the shift towards service-based economies, providing opportunities for India to benefit from further offshoring of manufacturing jobs from western economies. For those with suitable skills to be in employment, these structural shifts bring benefits in the potential gains to both productivity and average wages. Therefore, policy makers working with employers and education providers should invest in the types of education and training that will allow workers to adapt faster over time and reskill throughout their working life.

What research methodologies have been used to examine the impacts of Industry 4.0?

NSRD’s interest is in the impacts of Industry 4.0 on the economy, and on current and future skills. The research to be undertaken is a specific example of a *skills anticipation* exercise (see Chapter 2) – that is, the “use of labour market and skills information to predict and develop policy responses to future skills needs”.[1]

Foresight exercises and *skill assessments* are the methods of skills anticipation that have so far been most commonly used to investigate Industry 4.0 (see Chapter 4). Like preceding waves of technological change, Industry 4.0 can be considered a disruptive event, and there remains much uncertainty about its potential impacts. Consequently, foresight exercises are a suitable method for skills anticipation, drawing from a wide-range of quantitative and qualitative sources, and typically engaging with experts and stakeholders to develop and test alternative assumptions and scenarios about the future.

Of the research that estimates quantitative impacts of Industry 4.0, most calculate how many jobs will be vulnerable to automation by multiplying the (forecast) number of jobs in each occupation by a coefficient of ‘vulnerability to automation’ for that occupation. To calculate the coefficients of ‘vulnerability to automation’, each occupation is characterised by the activities and tasks performed, and a judgement made about the potential for automation of each activity/task. The studies reviewed used information for each occupation (e.g. activities to perform, skills required) from the US Department of Labour O*Net

[1]Skills panorama glossary: http://skillspanorama.cedefop.europa.eu/en/glossary/a, accessed 27/11/2017.

database to assess the 'vulnerability to automation'. This approach has been applied to India by McKinsey (2017) and by the Word Bank (2016) who found that the potential loss of jobs would be 52% and 42%, respectively. Even small changes in the methodology and assumptions made can lead to different estimates, even though most studies used the O*Net database as their starting point.

What research methodologies and tools are recommended for further research in India?

This *Foundation Report* makes recommendations about how the National Skills Research Division (NSRD) should take forward its own research into the potential impacts of Industry 4.0, on the economy, and on current and future skills in India (see Chapter 6).

NSRD is recommended first to review and refine the statement of the focus, rationale and logic for its research. It should describe more specifically what policy questions are to be answered, who are the relevant stakeholders, and what are their interests in the research. We recommend that NSRD complete a comprehensive review of datasets to assess if better sources of data for India are available than those we have identified in a brief review of data. Recommendations are made about how to identify and shortlist the priority sectors, how to analyse the likely impacts, how to engage and involve stakeholders, and how to draw and disseminate policy conclusions from the results.

1 Introduction

This Foundation Report recommends how the NSRD take forward its own research into the potential impacts of Industry 4.0

Technological change and innovation are key drivers of economic change. *Industry 4.0* is a term given to the current wave of technological change, underpinned by advances in the connectivity between humans and machines. There is much speculation about the nature and scale of the potential impacts of Industry 4.0; like previous industrial transitions, Industry 4.0 will have far-reaching implications for the way that we live and work.

Cambridge Econometrics (CE) has been commissioned by the British Council to prepare this *Foundation Report* to recommend how the National Skills Research Division (NSRD) should take forward its own research into the potential impacts of Industry 4.0, on the economy, and on current and future skills in India.

NSRD is a division within India's National Skill Development Agency (NSDA), which is an autonomous body under the Ministry of Skill Development and Entrepreneurship (MSDE). While NSRD will be the primary users of the *Foundation Report*, the findings will also be of interest to the MSDE and other stakeholders in India's skills system, as will be the further research to be undertaken by NSRD.

Three key questions are answered by this *Foundation Report*:

1. What is the evidence of the impact of Industry 4.0 from international research?
2. What research methodologies have been used to examine the impacts of Industry 4.0?
3. What research methodologies and tools are recommended for further research in India?

Defining Industry 4.0

Industry 4.0 is the fourth industrial revolution. The term is "applied to a group of rapid transformations in the design, manufacture, operation and service of manufacturing systems and products" (Davies 2015). It originated in Germany and the German Chancellor Angela Merkel defined it as "the comprehensive transformation of the whole sphere of industrial production through the merging of digital technology and the internet with conventional industry" (Davies 2015).

With respect to the manufacturing sector, McKinsey (2015) defines Industry 4.0 as "digitization of the manufacturing sector, with embedded sensors in virtually all product components and manufacturing equipment, ubiquitous cyber-physical systems, and analysis of all relevant data". PWC(2016) uses the term Industry 4.0 as the change driven by the digitisation and integration of vertical and horizontal value chains, the digitisation of product and service offerings, digital business models and customer access.

There is some variation in the definition of Industry 4.0 used in the various studies reviewed. For example, other labels used for Industry 4.0 are Internet of Things, Factory of Things, Factory of the Future or Smart Factories, all terms which are based on the new technological developments in information and communication technology (ICT), cyber-physical systems (sensors, robots, 3D printing), network communications. Simulation, big data and cloud computing, and artificial intelligence (AI). One broadly used term to describe the impact of Industry 4.0 on the economy, jobs and the labour force is *automation*. OECD (2017) defines automation of production as "the use of machines and automatic devices to perform part of the production process. It is generally used to reduce human intervention and is therefore considered to replace human labour by machines." For the purposes of this report, CE defines Industry 4.0 as the future digitalisation of the economy driven by the latest technological changes in ICT, cyber-physical systems, network communications, simulation, big data and cloud computing, and AI.

Skills anticipation to investigate the impacts of Industry 4.0 on current and future skills

NSRD's interest is in the impacts of Industry 4.0 on the economy, and on current and future skills. The research to be undertaken is a specific example of a *skills anticipation* exercise – that is, the "use of labour market and skills information to predict and develop policy responses to future skills needs".[2] This report has been informed by a review of both international evidence on the potential impacts of Industry 4.0 and of literature on methods in skills anticipation, and CE's own expertise in skills anticipation more broadly.

The structure of this report

Chapter 2 summarises different types of skills anticipation and their relevance to this research. To provide context and rationale for this research, Chapter 3 summarises the labour market landscape in India and the key challenges the country faces in the future. The findings from the literature review are synthesised in Chapter 4: the potential impacts of Industry 4.0; and the research methodologies used. Chapter 5 describes the type of data that is required for analyses and comments on the availability of data for India. Chapter 6 draws together earlier findings to make recommendations for the research strategy, methodologies and tools for research in India, and sets out the next steps for NSRD.

[2] Skills panorama glossary: http://skillspanorama.cedefop.europa.eu/en/glossary/a, accessed 27/11/2017.

2 The role of skills anticipation

2.1 Introduction

To help interpret and position the literature on Industry 4.0, it is helpful first to consider skills anticipation more broadly.

2.2 The rationale for skills anticipation

Gathering intelligence on current and future skill needs can inform better matching of skills

Skills anticipation is the "use of labour market and skills information to predict and develop policy responses to future skills needs".[3] Gaining a better understanding of the future is essential to inform decisions that involve long lead times, such as education and training, and long-term labour market planning. The world is changing rapidly, and although no-one can claim to be able to accurately predict the future, it is good practice to systematically assess future trends to improve the understanding of the potential risks and uncertainties, and to inform decision-makers. The research to be undertaken by NSRD is a specific example of a *skills anticipation* exercise; to assess the nature and scale of the potential impacts of Industry 4.0 on the economy, and on current and future skills. The findings from such exercises in skills anticipation are valuable to:

- fill existing information deficits and reduce future labour market imbalances
- inform various actors of future labour market needs (for example, information about demand for skills), as an aid to their choices and decision-making; and
- support policy-making in employment and social protection, education and lifelong learning (for example, by providing information about the economic returns to investing in education and training of different types)

2.3 Methods of skills anticipation

There are various methods of skills anticipation, designed to meet different needs and to make use of different evidence and data. These are described below and summarised in Table 2.1.

Skills assessments

Skill assessments (sometimes called skill audits) usually focus on a country, region, or sector. They review and collate existing evidence, sometimes including the assessments of experts and key stakeholders, to provide a comprehensive analysis of current skill needs and the implications of past trends for the future. To inform skills anticipation, it is preferable that skill assessments look beyond historical evidence to provide information about currently emerging and future skill needs. Typically, the findings can be both qualitative (e.g. a descriptive narrative of changing skill profiles within jobs) and quantitative (e.g. the changing number of people employed in an occupation, or with certain skills).

Skills forecasting

Skills forecasting refers to a systematic method of deriving quantified projections of future skill needs, usually over the next ten to twenty years. The projections provide a common and consistent economy-wide overview of skill needs, allowing detailed comparisons across sectors (and sometimes also

[3]Skills panorama glossary: http://skillspanorama.cedefop.europa.eu/en/glossary/a, accessed 27/11/2017.

regions). The findings can be used to answer questions, such as in which sectors and occupations will employment be growing; and for which qualifications will demand increase or decrease? Best practice involves the production of quantified projections using: a detailed multi-sectoral macroeconomic model; and modules to translate the results into implications for skills demand and supply (often measured in terms of occupations and qualifications).

Table 2.1: Alternative methods of skills anticipation

Method	Timespan	Advantages	Disadvantages	Examples
Skills assessment	Short, medium and long-term	Strong on (e.g. sectoral) specifics Synthesis of existing evidence	Partial Can be inconsistent across sectors and geographies	National Skill Development Corporation (NSDC) Industry reports https://www.nsdcindia.org/New/industry-reports
Skills forecasting	Medium-term	Comprehensive Transparent Consistent Quantified	Require much data Costly Not everything can be measured May give a misleading impression of precision	UK Working Futures skills projections https://www.gov.uk/government/publications/uk-labour-market-projections-2014-to-2024
Foresight	Medium and long-term	Holistic Long-term view, inclusion of disruptive events Direct 'user/customer' involvement	Non-systematic Can be inconsistent Can be very speculative and subjective	Russia "Skills 2030" – for sectors where technology is the primary driver of change in skills demand
Other: Qualitative investigations	Variable	Provide detailed information Direct 'user/customer' involvement	Not necessarily representative May be very subjective	Employer case studies, focus groups (interactive groups discussions to solve a problem or suggest ideas)
Other: Quantitative surveys	Short-term	Designed to answer specific questions	Myopic Can be costly (to obtain representative response)	Employer and employee surveys, tracker students (of recent students)

Source: Adapted from (ETF, ILO and Cedefop 2016).

Skills foresight

Skills foresights use qualitative methods to apply critical thinking about the future. Foresights are used to consider both short and long-term (referred to as 'horizon scanning') futures, and typically consider issues in a holistic way, considering uncertain and potentially disruptive events (events or technologies that change trends and the way things are done, such as Industry 4.0). Various methods can be used, such as, stakeholder discussions, commissioning papers by experts, and scenario development.

Other approaches

Other approaches to skills anticipation include: questionnaire surveys of employers about hard-to-fill vacancies and skills mismatches; tracker studies of students about their labour market outcomes; and analyses of the rates of return to investing in education or training (higher rates of return suggest high demand for skills).

As presented in Chapter 4, foresight exercises and skill assessments are the methods of skills anticipation that have so far been most commonly used to investigate the potential impacts of Industry 4.0.

3 The skills landscape in India

3.1 Introduction

To provide context for this report, this chapter gives a brief summary of the skills landscape in India.

3.2 India's labour force

India has an increasing supply of young but unskilled workers

India's labour force is characterised by a large supply of young but poorly-trained workers, and by low participation rates amongst women. The country's growing workforce is younger than the workforce in other advanced economies, but India is falling behind in developing its skills base (Ministry of Skill Development and Entrepreneurship 2015).

India has a young population around 54% (or 650million) of its total population is currently below 25 years of age. By 2020 it is estimated that the average age of the population in India will be 29 (compared to 40 in the USA, 46 in Europe and 47 in Japan) (British Council 2016). If properly trained, this supply of young workers could propel future economic growth and capitalise on the productivity gains from Industry 4.0.However, the Indian government estimates that only 5% of the total workforce has undergone formal skills training (compared to 68% in UK, 75% in Germany, 52% in USA, 80% in Japan and 96% in South Korea) (Ministry of Skill Development and Entrepreneurship 2015).

The average level of education is rising, but graduates are not ready to enter the job market

In general, enrolment rates for primary and secondary education have improved in the last years: 60% of 15-19-year-olds have received formal education or training, 30% have some level of education and 10% have never attended school (2011 Census data) (British Council 2016). The majority of people that have not received formal education are nevertheless in some form of employment, although typically in low-pay and low-skill jobs. On the other hand, unemployment is higher for graduates and those who have achieved higher skills level; around 8% of India's 77 million graduates with a diploma or a tertiary degree are unemployed, compared with 2% of non-graduates[4]. Moreover, it is younger graduates that are less likely to be employed: while 77% of those above 30 years of age holding a degree are employed, this figure is just 42% for those aged 18-29years. These figures suggest that poor quality higher education is holding back graduates from finding meaningful employment opportunities (KPMG 2016). Indeed, The National Employability report 2013 by Aspiring Minds estimates that 47% of Indian graduates are not employable for any industry role (Aspiring Minds 2013).

Few graduates are employable in high tech sectors

Graduates seem not to be well-suited for work in high-tech sectors. Of all graduates, 60% are in non-technical degrees (British Council 2017)(British Council 2016). Even technical graduates appear not to have the right skills. As an example, a low share of engineering graduates are employed in IT sectors:

[4]OGD Platform India, Incidence of unemployment by level of education: https://data.gov.in/catalog/incidence-unemployment-level-education-percentage, accessed 27/02/2018. Census of India, Population by level of education: http://www.censusindia.gov.in/2011census/C-series/C08.html, accessed 27/02/2018.

18% for IT Services, 4% for IT Products and 41% for Business Process Outsourcing. Moreover, only 4% of engineers qualify for a start-up technology role. These figures are attributable to the graduates' lack of the required skills: candidates have been found to have poor programming skills, take up few opportunities for training and to lack soft skills (Aspiring Minds 2016)[5].These figures are particularly worrisome in view of the disruptions that the new wave of technological development might cause. Industry 4.0 will create new roles requiring additional skilled workers, while existing jobs will be vulnerable to automation (McKinsey estimates that 52% of automatable activities in India will be vulnerable (McKinsey Global Institute 2017)). Hence, it is vital to train the labour force to avoid high unemployment and to exploit the opportunities offered by Industry 4.0.

Entrepreneurship, which could represent a source of innovation and of employment for young Indians, is also at quite low levels: India ranked 76 out of 143 countries in 2014 according to the Global Innovation Index, although it improved to 60 in 2017, and only 0.09 new companies were registered for every 1000 working age person in 2011(Ministry of Skill Development and Entrepreneurship 2015).

Many people work in the informal sector, and female participation is low

Some 93% of the workforce is in the informal/unorganised sector. The rate of job growth in the informal sector is estimated to be twice that in the formal sector (Ministry of Skill Development and Entrepreneurship 2015). Lack of information about the informal sector makes it a challenge to map skills to create more effective training programmes.

India's labour force is also characterised by a low and falling participation rate for women: from 33% to 27% in rural areas and from 18% to 16% in urban areas between 2004 and 2011 (Ministry of Skill Development and Entrepreneurship 2015). India ranks 10th from the bottom globally in terms of female labour participation (KPMG 2016). The World Bank estimated a labour force participation rate of 23% for women[6] and 79% for men in 2012.[7] Therefore, an active policy to improve women's access to employment opportunities is strongly needed.

3.3 India's training system

The training system has not been effective in increasing the quality of the labour force and its employment opportunities

Before the creation of the Ministry for Skill Development and Entrepreneurship (MSDE) in 2014, responsibility for vocational training was spread across 20 ministries, resulting in fragmentation of the training system and duplication of efforts. Training is delivered via a network of 9,400 Industrial Training Institutes (ITIs). ITIs have offered poor quality training, had serious infrastructure gaps, outdated curricula, high dropout rates and little contact with industry (FICCI, 2006). There is little evidence that ITI training improves employability; studies show little to no difference in wages between ITI

[5] The report defines employability as the result of a computer test performed by recent graduates in relation to benchmarking studies done at various companies in different sectors.

[6] World Bank, Labour force participation rate, female: https://data.worldbank.org/indicator/SL.TLF.CACT.FE.NE.ZS?locations=IN, accessed 27/02/2018.

[7] World Bank, Labour force participation rate, male: https://data.worldbank.org/indicator/SL.TLF.CACT.MA.NE.ZS?locations=IN, accessed 27/02/2018.

graduates and those who have completed only year 10 of schooling (Mehrotra et al, 2013).

Employers have reported as the main flaws in the training system a lack of practical experience and good quality trainers. Interestingly, employees report the same flaws, together with the lack of recognition of certifications by employers (British Council 2017).The National Skills Qualification Framework, implemented by the National Skill Development Agency in 2013, tries to solve the problem by creating a unifying and output-based reference to classify training programmes.

3.4 Future challenges and opportunities

Key sectors will see rapid expansion of employment

Recent GDP growth in India has been robust, supported by a steady increase in private consumption which created a higher demand for the service sector whose Gross Value Added grew at a rate of 10% per annum in 2014-2016(KPMG 2016). The World Bank forecasts that India's GDP will grow by 7% per annum over 2017-2019 (World Bank 2017). It is estimated that by 2022 sectors like Textiles and Clothing, Building and Construction Industry, Auto and Auto Components, Real Estate Services and Organised Retail will double their manpower requirement, compared with 2008 (British Council 2016).

Technological change will continue to shape the future skills required

Industry 4.0 will bring changes in consumption patterns and in the production process. The use of robots in manufacturing, of big data for business operations and consumer services, and of the internet as a marketplace replacing physical shops, are examples of such changes. Sectors such as retail, logistics, telecommunication and financial and professional services are going to feel the disruptive impact of new technologies (see Chapter4).

It is estimated that 37% of the workforce will be employed in jobs requiring radically different skill sets by 2022 (FICCI 2016).Therefore, it is crucial to provide the workforce with the necessary means in terms of skills and education to face those changes.

4 Assessing the impacts of Industry 4.0

4.1 Introduction

The findings synthesised in this chapter are drawn from a focused review of international evidence to investigate:

1. What is the evidence of the impact of Industry 4.0?
2. What research methodologies have been used to examine the impacts?

Only limited literature was found in the public domain from government/public bodies and specific to India

Efforts were made to find and include evidence pertinent to the client: with coverage of India and South Asia; and from independent organisations (e.g. national governments or international research institutions). However, only limited literature was found in the public domain from government/public bodies and specific to India. Included in the review was the best evidence that could be found; from government/public bodies (with comparable interests to those of NSRD), and relevant research from other bodies, such as business media and those that represent industry (see Appendix A1.11.1.1.1.Appendix A). It is acknowledged that some of the evidence, e.g. from business media and industry stakeholders, may represent a specific perspective. The research is trying to predict the future impacts of new and future (as yet unknown) technologies which have the potential to disrupt the economic system and to bring dramatic changes. The impacts will depend also upon the choices that businesses, society and government will make. Such research remains speculative and requires assumptions to be made based upon opinion and judgement. Nonetheless, valuable insights have been drawn and some key messages emerge.

A structured questionnaire was designed to identify and summarise the relevant information from each piece of research (see Appendix B).

4.2 Potential impacts

The impacts of automation on employment will vary across different sectors

One of the most significant impacts of Industry 4.0 is expected to be automation and its consequences for the numbers and types of jobs (see Table 4.1).

The potential impact of job automation in a country depends on the country's industry composition (i.e. the employment shares across sectors) and the relative proportion of jobs at high risk of automation in each of those sectors (PwC 2017). Automation is predicted to cause a serious decline in employment across many sectors but mainly on e-commerce, manufacturing, banking, agriculture, IT services and business process outsourcing (BPO) (Business Today (India) 2017).

Automation will not happen overnight since five key factors will influence the pace and extent of its adoption: technical feasibility, cost of developing and deploying solutions, labour market dynamics (including the supply, demand, and costs of human labour as an alternative to automation), economic benefits (labour cost savings) and social acceptance. While the effects of automation might be slow at a macroeconomic level within specific sectors or economies, they could be quite fast at a microeconomic level, for an individual worker whose activities are automated, or a company whose industry is disrupted by competitors using automation.

Table 4.1: Summary of sectoral impacts of Industry 4.0, based on literature review

Sector	Possible impact
Agriculture &Manufacturing	49% automation potential.
Manufacturing – textile	Replace 10,000 jobs with robots over three years.
Construction	56% automation potential.
Retail trade	67% automation potential.
Transportation and logistics	Decrease in employment due to autonomous vehicles and near real-time analysis of the distribution network[8].
IT	20-to-25% reduction in jobs in the industry over the next three years.
Finance	Automation has led to a significant reduction in financial transaction costs[9].
General services	14% decline for India's services industry by 2021.

More than half of jobs in India are thought to be vulnerable to automation

At the macroeconomic level, World Bank (2016) estimated that 42% of jobs are vulnerable to automation in India, while McKinsey (McKinsey Global Institute 2017) estimates the technically automatable activities at 52% (approximately 233 million full-time equivalent jobs associated with technically automatable activities). McKinsey estimates, the potential impact of automation by sector in India to be 49% of jobs in agriculture and manufacturing, 67% in retail trade, 56% in construction and 42% of other sectors. Moreover, in the manufacturing sector alone, 88% of occupations in production and 64% in transport can potentially be automated. These estimates are based on an assessment that some tasks in a job are more likely to be automated than others; they represent an estimate of the potential for automation, but without saying if and when this potential would be achieved.

Some expect the first major effect will be seen in manufacturing, IT and Information Technology Enabled Services (ITES), security services and agriculture (Bansal 2017). By 2021, at the global level four out of every ten jobs could disappear. Of these, one in every four jobs in India could be lost because of automation. Due to the differences in the labour market structures and the state of technology in the economy of each country and the methods used to obtain the estimate, the studies assessing the potential impact of automation have different results across countries. For example, the McKinsey report estimates the impact for India of 52%, for Japan 55% and for the United States 46% judging by their sector mix and the mix of activities within sectors.

Word Bank (2016) estimated that 69% of jobs in India have the potential to be automated. By using a different method to adjust for the technological feasibility and adoption time lags, World Bank estimated that the share of employment that could be automated is 42% while the OECD countries average is 57%[10].

Many low-skilled jobs in services will be vulnerable to automation…

A high impact of automation will be seen in the IT sector. In India, the IT sector was booming during recent years with many workers carrying out routine IT support work and repetitive back office tasks for global companies, tasks originally outsourced to India to take advantage of the cheaper labour. In view of Industry 4.0, a future increase in the IT sector will not mean the same

[8] Result not specific to India, but valid world-wide.

[9] Result not specific to India, but valid world-wide.

[10] The unadjusted figure is the same.

increase in jobs that was seen in the past. Rapidly improving automation threatens 20-25% of jobs in the IT sector in India over the next three years (Gent, Edd 2017).

In the services sector, according to the Horses for Sources future workforce impact model[11], India is set to lose 640,000 low-skilled positions by 2021, or 28%of jobs. Many customer-facing roles at the low-skill level are likely to be automated and consolidated. A key finding of the ILO report (Chang and Huynh 2016) indicates that women, workers with less education and workers in lower-wage occupation are more likely to be impacted by automation in ASEAN countries.

Using an occupations-based approach, Frey and Osborne (2013) quantified the potential extent of jobs at risk of computerisation for the US and found that service, sales and office jobs were likely to fall in the higher risk of automation category, while jobs in the broader sector of Education, Legal, Community Service, Arts and Media were estimated to have a low risk of automation. Moreover, the risk of automation is higher for low-skilled workers and for low-wage occupations.

…but low-skilled positions are not the only ones to be affected

Low-skill positions are not the only ones to be affected. Rapid improvements in technology will lead to the automation of jobs in medium-skilled activities such as accounting, clerical work and repetitive production tasks (OECD 2017). Therefore, the potential impact of job automation varies according to the characteristics of the workers (skills and education) and jobs (tasks, activities). For example, PWC (2017) found those with lower levels of education (GCSE-level and equivalent only or lower) are at greater risk of job automation, especially men, i.e. 46% (this contrasts with the ILO assessment that women are more likely to be impacted by automation in ASEAN countries).

Industry 4.0 is generating demand for new skills, and skills needs that will change more rapidly

Nevertheless, improvements in technology are also creating new job opportunities, especially in tech start-ups, e-commerce, and digital economy (NASSCOM 2017), and in the manufacture of the equipment required to facilitate Industry 4.0. Automation will take over some jobs but also create new ones. As technology embeds itself more deeply within different industries, the emphasis is shifting from scale of the industry to the skills of the workers. However, the challenge is that the lifecycle of skills is becoming shorter than ever. The skilled workforce has less time to market their acquired skills before they need re-skilling.

According to NASSCOM (2017), the requirement for tech skills will diffuse across a growing number of economic sectors. Moreover, technical competencies (especially in new technologies) and soft skills will be in demand. It is assumed that 50-60% of jobs would require new skills such as big data analytics, cloud and cyber security services, Internet of Things, service delivery automation, robotics, AI/machine learning/ Natural Language Processing (NASSCOM 2017). Therefore, policy makers should focus on new-age skills that are in demand globally by continuously refreshing skills and fill the growing global skill gap. Moreover, in view of the latest cyber security

[11]Automation Impact: India's services industry workforce to shrink 480,000 by 2021 - a decline of 14% (2016): https://www.horsesforsources.com/indias-services-industry-set-to-lose-640000-low-skilled-jobs-to-automation-by, accessed 27/02/2018.

incidents, cyber security skills, technologies, practices and research should be given higher importance.

Industry 4.0 has the potential to raise productivity, and average wages

Another positive outcome from automation is the increase in productivity. McKinsey (2017) estimated that automation could raise productivity growth globally by 0.8-1.4% annually. A move away from employment in routine tasks to more complex ones will shift the occupational structure of industries, with the potential to raise both productivity and average wages. It is possible that automation might lead to higher average real income levels across the country due to higher overall productivity (PwC 2017).

Responding to the challenges and opportunities

To reduce workers' exposure to offshoring from higher labour cost countries (relocation of production to other countries), OECD (2017) recommends that investing in skills development is important and the same recommendation is made by the World Economic Forum (2016) with respect to future technological transformations. Countries need to invest in both education and training, and to make better use of skills, and better co-ordinate skills-related policies. This is relevant also in countries such as India that have the opportunity to benefit from offshoring if they can offer suitably skilled lower-cost workers. Policy makers, working with employers and education providers, should invest more in the types of education and training that will be most useful to people in this increasingly automated world (PwC 2017). For example, efforts to place unemployed youth in apprenticeships in certain job categories through targeted skills training may be self-defeating if skills requirements in that job category are likely to be drastically different in just a few years' time (World Economic Forum 2016). This situation is already reflected in India by FICCI (2016) who reports that as the job market transforms, students are already finding it increasingly difficult to keep up with the pace of the evolving skill requirements.

The WB development report (World Bank 2016) suggests that governments should make the internet universally accessible and affordable to increase the digital skills of workers. This task can be achieved through a judicious mix of market competition, public-private partnerships, and effective regulation of the internet and telecom sector. A harder task will be to ensure that the internet remains open and safe as users face cybercrime, privacy violations, and online censorship.

4.3 Methods used to assess impacts

Foresight exercises and skill assessments, using a mixture of both quantitative and qualitative methods, are the methods of skills anticipation that have so far been most commonly used to assess the impacts of Industry 4.0 or automation on the economy.

*US Department of Labour O*Net database provides a framework to characterise activities of each occupation*

All the studies reviewed used information from the US Department of Labour O*Net database to assess the automation risk that an occupation might have. This database is the most detailed and comprehensive existing database on occupations, containing key features of all occupation as a standardised and measurable set of variables and open-ended descriptions of specific tasks for each occupation. The database is specific to the US, so by applying it to other countries the researchers are assuming that the characteristics of an occupation in, say, India are the same as those of that occupation in the US.

McKinsey (2017) used a methodology based on the state of technology with respect to 18 performance capabilities to estimate the technical automation potential of more than 2,000 work activities in more than 800 occupations across the US economy using data from the US Department of Labour (2014 O*Net database). By estimating the amount of time spent on each of these work activities, it was possible to estimate the automation potential of occupations in sectors across the economy, comparing them with hourly wage levels. Drawing on industry experts, scenarios were developed for how rapidly the performance of automation technologies could improve in each of these capabilities. This analysis was then used as a template for estimating the automation potential and creating adoption timing scenarios for 45 other economies representing about 80% of the global workforce.

Similar analysis using the US O*Net database was done by Frey and Osborne (2013), Arntz et al (2016) and PWC (2017). Frey and Osborne (2013) assessed how susceptible jobs are to computerisation[12] (i.e. to developments in machine leaning and mobile robotics) by implementing a novel methodology to assess the probability of computerisation for 702 detailed occupations, using a Gaussian process classifier. First, occupations were categorised according to their susceptibility to computerisation; using experts' opinion, occupations were categorised based on the variety of tasks they involve, assigning 1 if automatability was possible, and 0 if not. Thus, 70 out of 702 occupations are considered by experts computerisable. The levels given in O*Net survey for perception and manipulation (i.e. finger dexterity, manual dexterity, cramped work space, awkward positions), creativity (i.e. originality, fine arts), and social intelligence (i.e. social perceptiveness, negotiation, persuasion, assisting and caring for others) required in the performance of occupation were then used to define indicators of bottlenecks to computerisation, i.e. tasks that cannot be defined in terms of codifiable rules and hence having a lower risk of being automated with the current technology[13]. This step was used to determine how difficult is for the 632 occupations left to assess to be automated. For this purpose, an algorithm was used to predict the probability of automatability as a function of variables supplied by O*Net for each occupation. This information is then combined with employment data by occupation to estimate the number of jobs that are in the high risk of automation category.

Methods that take account of the tasks performed in each job estimate a lower overall risk of automation

Starting from the occupational-based approach of Frey and Osborne (2013), Arntz et al. (2016) developed a task-based approach to estimate the risk of automation for jobs in 21 OECD countries. The study also used O*Net databases under the assumption that occupations in OECD countries are comparable to US occupations. The approach is based on the idea that the automatability of jobs ultimately depends on the tasks that workers perform for these jobs, and how easily these tasks can be automated. Therefore, applying a task-based approach results in a much lower risk of automation compared to the risk estimated by the occupation-based approach of Frey and Osborne (2013). The difference between the two approaches is driven by the fact that in occupations considered by Frey and Osborne to be in the high-risk category, workers would also perform tasks that to some extent are difficult to

[12]Frey and Osborne (2013) define computerisation as "job automation".

[13] Only the technical capability of automating tasks was assessed and not its economic feasibility.

automate, i.e. tasks involving face-to-face interaction. Moreover, Arntz et al. (2016) used individual survey data (the Programme for the International Assessment of Adult Competencies (PIAAC)) to take into account of individuals within the same occupation that often perform quite different tasks. For this reason, self-reported tasks by individuals are likely to be a better indicator of workers' actual tasks.

The task-based approach consists of estimating the relationship between workers' tasks and the automatability of jobs in the US, i.e. matching the automatability indicator from Frey and Osborne (2013) to the US observations in the PIAAC data based on the occupational codes. Since the PIAAC data is available only at 2-digit ISCO codes, then multiple imputation approach (Expectation-Maximization algorithm) is used to assign multiple values of the automatability to each individual in the PIAAC data. The Expectation-Maximization algorithm regresses first the automatability on the N characteristics of the jobs. The model thus shows which explanatory variables influence the automatability in the US and these variables are then used to predict automatability in other OECD countries. The outcome is the jobs (and not occupations) that are likely to be exposed to automation, since the analysis takes into account the tasks performed in those jobs. So, jobs with larger shares of automatable tasks are more exposed to automatability than jobs with larger shares of non-automatable tasks; hence only 9% of jobs in OECD countries are estimated to be potentially automatable rather than 47%, as proposed by Frey and Osborne (2013).

This approach requires detailed information by occupation, tasks and skills. Any of the methods presented above can be used if the data is available. The Survey of Adult Skills (PIAAC) from OECD can be used as an example of what type of data should be collected to understand the individual's tasks by occupation but also the skills required to perform the tasks. In addition to helping to assess the potential impact, this data can be used also to design training programmes to skill and re-skill the workforce in occupations or sectors that will be facing the highest threat from automation.

PWC (2017) replicated the approaches used both by Arntz et al. (2016) and Frey and Osborne (2013). PWC (2017) enhanced and recalibrated their model and obtained UK and US results that were closer to Frey and Osborne (2013) than to Arntz et al. (2016). For example, for the UK, the proportion of jobs potentially at high risk of automation is 30% according to PWC (2017), 35% according to the occupation based-approach developed by to Frey and Osborne (2013) and 10% according to the task-based approach used by Arntz et al. (2016). Therefore, even small changes in methodology can lead to different results although all three studies used the O*Net database as their starting point.

Taking account of other factors that influence automation

The research methodology developed by Frey and Osborne (2013) is used by Chang and Huynh (2016) in assessing how susceptible occupations are to automation in the ASEAN countries[14]. For this purpose, the automation probabilities presented in the original Frey and Osborne study (2013) were applied to the labour force survey data and the percentage of workers at high risk of automation were estimated as follows: Cambodia 57%, Indonesia 56%,

[14]Cambodia, Indonesia, the Philippines, Thailand and Vietnam.

the Philippines 49%, Thailand 44% and Vietnam 70%. In addition, the econometric relationship between the risks of automation with two other factors: educational attainment and earnings was examined. Furthermore, a standard logistic regression model was used to quantify the probability of being employed in a high-risk occupation for different socio-demographic indicators such as sex and age.

Foresight exercises to assess future trends

The World Economic Forum report (2016) looked at the changes driven by a Fourth Industrial Revolution to understand the current and future impact of key disruptions on employment levels, skill sets and recruitment patterns in different industries and countries and to stimulate deeper thinking about how business and governments can manage this change. This analysis was based on O*Net labour market information system and data collected via a survey of Chief Human Resources Officers and other senior talent and strategy executives of leading global employers, representing more than 13 million employees across 9 broad industry sectors in 15 major developed and emerging economies and regional economic areas. The survey was designed to understand the possible expectations regarding the future of jobs, work and skills by the largest employers to provide an evidence base and guidance to businesses, governments and civil society organizations such as labour unions and education providers. The respondents of the survey identified the following technological-related drivers of industrial change: mobile internet, cloud technology; processing power, big data; new energy supplies and technologies, internet of things, sharing economy, crowdsourcing; robotics, autonomous transport; artificial intelligence; advance manufacturing and 3D-printing; advance materials and biotechnology. The survey respondents considered all these drivers as having a profound impact on the employment landscape over the coming years. In addition, based on the results of the survey, the future of jobs and the pace of change to the global employment landscape up until the year 2020 was estimated.

Surveys to anticipate skills

Using existing surveys on skills and occupations it is possible to draw conclusions on the readiness of the labour force in the face of automation. For example, using the European Skills and Jobs Survey (ESJS), Cedefop (2017) examined the job substitution due to technological change, the existence and use of digital skills and other skills required in the face of technological advancement. The survey results indicated that around 10% of adult workers in the EU are at high risk of technological skills obsolescence. Around 21% of adult employees (30% of those working in ICT services) think it very likely that several of their skills will be outdated in the next five years. Moreover, despite the spread of technology in the EU, the survey also shows that a high share of the EU workforce is excluded from the digital economy meaning that a high proportion of the EU population has low digital skills or do not use the internet.

Sector skill assessments

A series of ‘Industry reports’ produced by KPMG, commissioned by the National Skill Development Corporation (NSDC), aim to identify the current state of 24 industries, their key drivers of growth and the skills needed to meet future trends[15]. This approach collates quantitative information from various sources, like the number of employed persons, revenue figures, or share of graduates, along with more qualitative observations, used to provide a narrative explaining the state of the industry and to outline the trends (to 2022)

[15] See NSDC Industry Reports: https://www.nsdcindia.org/New/industry-reports, accessed 27/08/2018.

potentially affecting the skills requirements. A similar analysis is also performed at the sub-sectoral and geographical level, showing the characteristics and trends shaping the industry's sub-sectors and its main hubs. Technological change is identified as a key driver shaping future skills, for instance in industries such as retail and construction, where online retail and increased mechanisation are calling for a more technologically proficient workforce.

The reports also present estimates of the composition of the workforce and expectations about future employment, listing the main job roles in the industry together with the skills requirements and current skill gaps, described in a qualitative fashion. Significant shortages of skills and a lack of proper training are found in several sectors along with opportunities for further development. These figures are drawn from reports produced by the government, trade associations or other consultancies, together with primary interviews with relevant stakeholders. To assess the potential supply of skills, the educational system is reviewed, and comparisons made with the trends in demand. Recommendations are made for key stakeholders, such as the government, educational institutions and corporates, for examples in the retail industry, it is recommended to introduce mandatory IT courses to support technology-enabled initiatives.

4.4 Summary of findings from the literature review

What is the evidence of the impact of Industry 4.0 from international research?

Industry 4.0 is likely to accelerate structural changes in the Indian economy. Some sectors and occupations are likely to be more impacted than others based on the economic barriers to automation, the education level and skills of their workforce, the nature of the tasks and activities of jobs and how labour intensive the sector is. The pace of automation will depend on the relative costs of robots (including energy inputs, maintenance and repairs) relative to human workers, as well as their relative productivity. In higher-cost western economies, Industry 4.0 is expected to accelerate the shift towards service-based economies, providing opportunities for India to benefit further from offshoring of manufacturing jobs from western economies. For those with suitable skills to be in employment, these structural shifts bring benefits in the potential gains to both productivity and average wages. Therefore, policy makers working with employers and education providers should invest in the types of education and training that will allow workers to adapt faster over time and reskill throughout their working life.

What research methodologies have been used to examine the impacts of Industry 4.0?

Foresight exercises and skill assessments are the methods of skills anticipation that have so far been most commonly used to investigate Industry 4.0. Like preceding waves of technological change, Industry 4.0 can be considered a disruptive event, and there remains much uncertainty about its potential impacts. Consequently, foresight exercises are a suitable method for skills anticipation, drawing from a wide-range of quantitative and qualitative sources, and typically engaging with experts and stakeholders to develop and test alternative assumptions and scenarios about the future.

Of the research that estimates quantitative impacts of Industry 4.0, most calculate how many jobs will be vulnerable to automation by multiplying the (forecast) number of jobs in each occupation by a coefficient of 'vulnerability to automation' for that occupation. To calculate the coefficients of 'vulnerability to automation', each occupation is characterised by the activities and tasks performed, and a judgement made about the potential for automation of each activity/task. This approach has been applied to India by McKinsey (2017) and by the Word Bank (2016) who found that the potential loss of jobs would be 52% and 42%, respectively. Even small changes in the methodology and assumptions made can lead to different estimates, even though most studies used the O*Net database as their starting point.

The next Chapter summarises the type of data that has been, and could be used, to estimate the impacts of Industry 4.0 in India.

5 Data requirements

5.1 Introduction

This chapter summarises the type of data that has been, and could be used, to estimate the impacts of Industry 4.0 in India. The next chapter makes recommendations for methodologies to be used by NSRD and the data required.

5.2 Relevant datasets

Datasets used in the literature reviewed

The literature review identified a variety of methods and sources, and the datasets used have been reviewed. The literature based on more quantitative methods were largely based on international datasets (e.g. OECD, UN, ILO). These have been summarised in Table 5.1. These data can be used as an example of what type of data should be collected. For example, the Survey of Adult Skills (PIAAC) from OECD can be used as an example of what type of data should be collected to understand the individual's tasks by occupation and the skills required to perform the tasks.

India-specific datasets

Following on from the literature review, India's national datasets were reviewed to identify data sources for key variables specific to India and its states. Table 5.2 provides a summary of the relevant Indian datasets identified. This is not a complete list and as part of the next steps, it would be valuable for NSRD to investigate the sources of the data identified in Table 5.2, as well as any additional national datasets not mentioned, to get a better understanding of their coverage and suitability. Future studies would benefit from the use of more comprehensive datasets with better breakdowns by state, more detailed sectors and a fuller time series.

Challenges

As mentioned previously, a large proportion of India's workforce is employed in the informal economy, and so one important issue to address in the data is the representation of India's informal sector. It is a challenge to measure the informal sector, and one that is attempted by the Informal Sector and Conditions of Employment in India[16] report. The report includes estimates of the number of workers in the informal sector by sector and by state, and it will be useful to incorporate these data in future analysis on the potential impacts of Industry 4.0 on the economy and on current and future skills in India.

Data requirement of skills forecasting

As discussed in Chapter 2, *skills forecasting* is one possible approach to skills anticipation. Best practice in *skills forecasting* involves the production of quantified projections using: a detailed multi-sectoral macroeconomic model; and modules to translate the results into implications for skills demand and supply (often measured in terms of occupations and qualifications).

Economic forecasts are an important element needed to estimate the impacts of Industry 4.0. The risk of automation is higher in certain sectors and occupations, and forecasts for many of the key variables in Table 5.2 would be valuable. In particular, forecasts for employment by sector and occupation will

[16] The Employment and Unemployment Surveys of the National Sample Survey (NSS), 2009 – 2010, (2012): http://www.mospi.gov.in/sites/default/files/publication_reports/nss_rep_539.pdf, accessed 27/02/2018.

provide an indication of a sector's future size and composition, which can be used to help assess its exposure to automation in the future. It would be beneficial if the forecasts were produced by a single macroeconomic model for India (to ensure consistency and comparability). This is a large and separate undertaking in itself, and so Table 5.2 identifies two sources of employment and population projections that may be useful as a starting point in the absence of more comprehensive macroeconomic forecast.

Summary of data requirements

In summary, it would be valuable to have access to the following timeseries data by state to use in future research on the impacts of Industry 4.0 in India:

- Employment by 2-digit NIC sector (including projections)
- Employment by 2-digit NCO occupations (including projections)
- Employment by 2-digit NIC and NCO
- Enterprises by sector and size
- Employment in the informal economy by sector
- GVA by 2-digit NIC sector
- Wages by 2-digit NIC sector
- Population by age and gender (including projections)
- Economic activity (employed, unemployed, inactive) by age and gender
- Education (qualifications) by age and gender

Table 5.1: Review of international datasets

Dataset	Description	Geographical coverage	Time coverage	Dimension	Access
O*Net	Contains hundreds of standardized and occupation-specific descriptors on almost 1,000 occupations covering the entire U.S. economy	USA	No time dimension	Description of occupations over several dimensions, e.g. activities to perform, skills required, work context, wages.	O*Net OnLine (link)
World Development Indicators	The primary World Bank collection of development indicators, compiled from officially-recognized international sources	National, regional and global estimates	Annual, from 1960 to 2016	Topics covered include: Agriculture & Rural Development, Economy & Growth, Education, Labour & Social Protection, Poverty, and Science & Technology.	World Development Indicators (link)
OECD Trade in Value Added (TiVA)	Indicators considering the value added by each country in the production of goods and services that are consumed worldwide	63 economies covering OECD, EU28, G20, most East and South-east Asian economies and a selection of South American countries	Annual, from 1995 to 2011	Variables include: value added content of gross exports and imports and Value added by origin.34 unique industrial sectors are represented, including 16 manufacturing and 14 services sectors.	OECD (link)
OECD Productivity Statistics	Various indicators of productivity	50 countries	Annual, 1970-2016 depending on the indicator	Variables include: GDP per hours worked and unit labour cost.	OECD (link)
ITU Statistics	Data about the usage of internet and communication technology	Global	Annual, from 2000 to 2016	Variables by country include: fixed-telephone subscriptions; mobile-cellular subscriptions; percentage of individuals using the Internet; fixed-broadband subscriptions; core indicators on access to and use of ICT by households and individuals; Gender ICT statistics	ITU (link)

Dataset	Description	Geographical coverage	Time coverage	Dimension	Access
United Nation Population Division	Data about various demographic trends	Global	Annual, from 1950 to today, with projections for future decades	Variables include: population by age and sex, dependency ratio and life expectancy.	United Nation Population Division (link)
ILO	Various Labour and Employment indicators	Global	Annual, quarterly and monthly, from 1948 (depending on the indicator) to today with projections	Breakdowns include: gender; economic activity; age; occupation and sector. Other variables include labour force participation rate.	ILOSTAT (link)
The Survey of Adult Skills (PIAAC)	The survey measures adults' proficiency in key information-processing skills - literacy, numeracy and problem solving in technology-rich environments - and gathers information and data on how adults use their skills at home, at work and in the wider community	Covers about 40 countries (excluding India)	Three rounds: Round 1 (2008-2013); Round 2 (2012-2016); Round 3 (2016-2019)	The dataset includes several variables, and breakdowns include: age, education level; level of experience; labour force status, etc.	OECD website (link)

Table 5.2: Review of relevant Indian datasets

Dataset	Description	Geographical coverage	Time coverage	Dimension	Access
Employment in Organised Sectors	Provides employment figures by9 sectors from the Ministry of Finance and the Department of Economic Affairs	India total - excludes Sikkim, Arunachal Pradesh, Dadra & Nagar Haveli and Lakshadweep	1995, 2000, 2003 to 2011	Includes a public/private sector breakdown.	Open Government Data Platform (OGD) India (link)
Employment - Unemployment Survey	Results of an employment survey for particular years	India by state	2011-12 2015-16	• Employment by 20 industries and state • Employment by 4-digit industries for India (2011-12)	India - Employment and Unemployment Survey 2011-2012, with ILO standard variables (link)

Dataset	Description	Geographical coverage	Time coverage	Dimension	Access
				• Employment by 9 occupations and state • Employment by 27 occupations and gender for India (2011-12) • Labour force participation rate by gender and state • Population by age, gender and state	Fifth Annual Employment – Unemployment Survey (2015-16) (link)
National Accounts	Gross Value Added by economic activity	GVA by sector for India as a whole. Total GVA by state.	National Accounts Statistics – 2017 has data from 2011-12 to 2015-16.	• GVA by 25 sectors for India. • Total GVA by state (i.e. no sector breakdown).	Statement 1.6 - Gross Value Added by economic activity at current and constant prices Statement 4.1 Value added by central and state governments (link)
The Talent Demand-Supply Analysis	Highlights qualitative and quantitative trends and insights to bridge the Talent Demand-Supply requirements and impact policy, operational and decision making	Some information by key Indian states.	2013 and 2016	Demand and supply side analysis. Some gender and state breakdown.	Sector Skill Councils (link)
National Policy on Skill Development and Entrepreneurship	Projections of employment by sector and state	India by state	Requirement from 2012/13 to 2022	Breakdown by sector and state.	National Skills Development Corporation report (Appendix-I of National Policy on Skill Development and Entrepreneurship).
Area and Population - Statistical Year Book India 2016	Population projections	India	2016, 2021, 2026	Breakdown by 17 agebands and gender.	Ministry of Statistics and Programme Implementation – Statistical Year Book India 2016, Area and Population (link)

6 A research strategy for India

6.1 Introduction

The main purpose of this *Foundation Report* is to inform the NSRD about how to proceed with its own research to assess the potential impacts of Industry 4.0, on the economy, and on the current and future demand for skills in India. This chapter draws together findings from the preceding chapters, and CE's own expertise, to make recommendations for the strategy, methodologies and tools for research in India.

6.2 Make clear the logic to frame the research

Prior to embarking on any research, it is good practice to clearly state the rationale and logic for the research. This should include statements of: the context; the policy questions to be answered; and the relevant stakeholders and their interests in the research. As set out in this *Foundation Report*, in brief, CE understands the purpose of NSRD's further research is as follows.

Skills anticipation is an important activity of NSRD

NSRD is a division within India's NSDA, which is an autonomous body under the Ministry of Skill Development and Entrepreneurship (MSDE). NSRD is required to provide policy inputs to the MSDE, NSDA, National Skill Development Corporation (NSDC) and related bodies in the skills domain. To provide policy inputs, an important activity of NSRD is that of *skills anticipation* – that is, the "use of labour market and skills information to predict and develop policy responses to future skills needs".[17] In the skills domain, gaining a better understanding of the future is essential to inform decisions that involve long lead times, such as education and training, and long-term labour market planning.

Looking to the future, the world is changing rapidly. Over many centuries, technological change and innovation have been key drivers of economic change. *Industry 4.0* is a term given to the current wave of technological change, underpinned by advances in the connectivity between humans and machines. There is much speculation about the nature and scale of the potential impacts of Industry 4.0; like previous industrial transitions, Industry 4.0 will have far-reaching implications for the way that we live and work.

Policy questions to be answered

The purpose of the research to be undertaken by NSRD is to assess the nature and scale of the potential impacts of Industry 4.0 on the economy, and on current and future skills. Examples of policy questions to be answered include:

- what types of impact will there be, and how large will they be?
- where will the impacts be greatest (sectors, occupations, states)?
- how will the impacts vary across different parts of the labour force/population (for example, the inactive, the low-skilled, those without formal education)?

[17] Skills panorama glossary: http://skillspanorama.cedefop.europa.eu/en/glossary/a, accessed 27/11/2017.

We recommend that NSRD reviews and refines the material in this *Foundation Report* to develop a clear statement of the focus, rationale and logic for its research. It should describe more specifically, what are the policy questions to be answered, who are the relevant stakeholders, and what are their interests in the research.

6.3 Identify the sectors on which to focus the research

The review of international literature undertaken for this *Foundation Report* has gathered initial evidence about the types of impacts of Industry 4.0 and the sectors (and/or occupations) likely to be most vulnerable to impacts.

There will be a process of transition as Industry 4.0 diffuses across economies. The pace and extent of its adoption in each economy will be influenced by various factors, such as: technical feasibility, cost of developing and deploying solutions, labour market dynamics (including the supply, demand, and costs of human labour as an alternative to, or support for, automation), economic benefits (labour cost savings) and social acceptance. While the impacts of Industry 4.0 might not be obvious at a macroeconomic level, within specific industry sectors, they will be more distinct.

One of the most significant impacts of Industry 4.0 is expected to be automation and its consequences for the numbers and types of jobs; much of the existing research has sought to estimate the potential scale of job losses. The potential impact of job automation in a country is driven by its industry composition (i.e. the employment shares across sectors) and the relative proportion of jobs at high risk of automation in each of those sectors.

Automation will have significant impacts on several sectors

The international evidence (see Chapter 4) suggests that more than half of formal-sector jobs in India are thought to be vulnerable to automation. All sectors are likely to be affected and those sectors most at risk are:

- Manufacturing
- Agriculture
- Transport
- Retail
- Accommodation and food services
- Construction

The potential impact of job automation varies according to the characteristics of the jobs (tasks, activities) and this has consequences for the vulnerability of different types of workers. Jobs which comprise collecting and processing data and predictable physical activity are more vulnerable. Consequently, the risk of automation is higher for low-skilled workers and for low-wage occupations. Nonetheless, low-skills positions are not the only ones to be affected; rapid improvements in technology will lead to the automation of jobs in middle-skilled activities such as banking, accounting, clerical work and repetitive production tasks.

Improvements in technology are also creating new job opportunities, especially in tech start-ups, e-commerce, and the digital economy. As technology embeds itself more deeply within different industries, the emphasis is shifting from scale of the industry to the skills of the workers. However, the challenge is that the lifecycle of skills is becoming shorter than ever (see

Chapter 4). The skilled workforce has less time to market their acquired skills before they need re-skilling.

In higher-cost western economies, Industry 4.0 is expected to accelerate the shift towards service-based economies, providing opportunities for India to benefit from offshoring. For those with suitable skills to be in employment, these structural shifts bring benefits in the potential gains to both productivity and average wages.

Assess which sectors are important in the economy

Given this initial list of sectors that are likely to experience significant impacts of Industry 4.0, we recommend that the NSRD further refines the focus by assessing which sectors are most important (now, or in the future) for India. There are various criteria by which the importance of a sector can be judged, as discussed below.

We recommend that NSRD reviews policy documents (or consults with other Ministries) of the government to identify those sectors that have been judged to be of strategic importance to the Indian economy. For example, the Make in India[18] initiative lists several priority sectors including automobiles, chemicals, IT, pharmaceuticals, textiles, ports, aviation, leather, tourism and hospitality, wellness, railways, auto components, design manufacturing, renewable energy, mining, bio-technology, and electronics.

As outlined in Chapter 5, we recommend also that NSRD gathers data about the size and composition of sectors to interpret in the context of India's identified policy priorities. Information about size and composition can be used to help assess a sector's importance. NSRD should collate data (see Chapter 5) to measure how many people are employed in each sector, both now and in the future, and also how much value added output the sector generates. In addition, collate data to analyse the characteristics (e.g. age, gender, education-level, location) of people employed in each sector and the distribution of the size of enterprises in each sector.

These measures of sector size and composition need to be interpreted in the light of the labour market context and policy priorities of India. For example, a sector whose firms are located in an area of high unemployment or that are potential employers of women or the young may be of importance if there is a policy priority to reduce unemployment or increase employment of women or the young. Similarly, if there are initiatives to harness the contribution of MSMEs[19], sectors with a relatively high proportion of MSMEs will be of importance.

This further analysis will shortlist and refine (e.g. which specific sectors within manufacturing) the priority sectors on which to focus the research.

6.4 Analysis of the sectors

In this section we recommend the research methodologies and tools to be used to analyse the sectors.

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[18]Make in India website: http://www.makeinindia.com/home

[19] Micro, small and medium enterprises.

Economy-wide assessment of vulnerability to automation

An approach identified in the literature is to make an economy-wide assessment of vulnerability to automation. The number of jobs vulnerable to automation is estimated by multiplying the (forecast) number of jobs in each sector/occupation by a coefficient of 'vulnerability to automation' for that sector/occupation. This approach has been applied to India by McKinsey (2017) and by the Word Bank (2016) who found that the potential loss of jobs would be 52% and 42%, respectively (see Chapter 4).

We recommend that NSRD replicates this approach to make an economy-wide assessment of vulnerability to automation. The benefits of doing so include:

- The process of collating the data and inputs, and doing the analysis, will not only build a useful evidence base, it will give valuable experience in research methods.
- The approach makes estimates for all sectors of the economy and so provides benchmarks and context in which to further investigate the priority sectors.
- The data and assumptions can be tailored to the case of India (for example, by tailoring the 'vulnerability to automation' coefficients, or by developing estimates at state level).
- The approach provides a framework to engage and involve stakeholders, to benefit from their insights, to add credibility, and to extend 'buy-in' to the research.

We recommend that NSRD follows a staged approach as summarised in Table 6.1. The recommended sources of data for India that are listed in Table 6.1 are informed by the brief review of data that was done for this report. As stated in Chapter 5, we recommend that NSRD complete a comprehensive review of datasets to assess if better sources of data for India are available.

We recommend that data processing and calculations are performed in Excel, using formulae, to set out a clear logic (and audit trail) that is transparent and can be easily understood, checked and updated (e.g. with updated data, or revised coefficients).

Table 6.1: Staged approach to economy-wide assessment of vulnerability to automation

Stage	Method	Source for 'number of jobs'	Source for 'vulnerability to automation' coefficients
1. Proof of concept	Replicate the approach using past jobs data for India and McKinsey's 'vulnerability to automation' coefficients. • Gather data for the number of jobs by sector (and ideally also by occupation) in India. Consider a suitable sector aggregation to use – for example, review sector aggregations that are available for: jobs forecasts (see Stage 2); state-level data (see Stage 4). • McKinsey's 'vulnerability to automation' coefficients are available by 'Sectors by activity type'. Assess how the McKinsey sectors correspond to the sectors available in the India data; map the corresponding coefficient to the sectors for India. • Multiply the number of jobs in each sector by the coefficient of 'vulnerability to automation' for that sector. • Add up the sector impacts to estimate the total impact.	India national data: Employment - Unemployment Survey	Exhibit E4: Technical potential for automation across sectors (% automation per sector). Source: McKinsey Global Institute (2017) A future that works: automation, employment, and productivity.
2. Future-looking estimates	Replicate the approach using jobs forecasts for India and McKinsey's 'vulnerability to automation' coefficients. • Gather data for the forecast number of jobs by sector (and ideally also by occupation) in India. • Multiply the number of jobs in each sector by the coefficient of 'vulnerability to automation' for that sector. • Add up the sector impacts to estimate the total impact. • Compare and interpret the results of Stages 1 and 2 with the estimates from other sources (e.g. McKinsey and World Bank, see Chapter 4).	National Skills Development Corporation report (Appendix-I of National Policy on Skill Development and Entrepreneurship).	See Stage 1.
3. Refine the 'vulnerability to automation' coefficients	McKinsey's 'vulnerability to automation' coefficients are based on the US Department of Labour O*Net database. This means that an implicit assumption is being made that an occupation in India has the same characteristics (e.g. activities to perform, skills required) as the same occupation in the USA, and this is determining the assumptions about that occupation's 'vulnerability to automation'. We recommend that NSRD engages with stakeholders to gather evidence to review and refine the 'vulnerability to automation' coefficients. • Focus the exercise (at least initially) on the priority sectors.	Same as Stages 1 and 2.	Tailor the coefficients using evidence and opinion of stakeholders.

	• Identify relevant stakeholders to engage in discussions about the nature of jobs, their tasks and skills, and potential vulnerability to automation. Relevant stakeholders could include: Sector Skill Councils; employers; and experts in the field of technological change. Consult NSDC to find out which relevant stakeholders were involved in the production of the NSDC 'Industry reports'. • Host a workshop with the stakeholders. Present to the stakeholders the existing assumptions and how they were derived (from Stage 1). Ask if stakeholders agree or disagree to the assumed coefficients, and to provide a rationale for their opinion (based on the likely skill/task requirements). • Collate the stakeholder evidence and assess whether or not, and to what extent, to revise the assumptions. • Recalculate the impacts using the revised assumptions. Share the results with the stakeholders and engage them in the interpretation and dissemination of results.	
4. Extend the detail of the analysis	We recommend that NSRD consider extending the detail of the analysis, for example to look at the different states of India, or to disaggregate by gender. This would be a straightforward exercise if data (and forecasts) for India can be obtained disaggregated by sector (and occupation) and state, or sector (and occupation) and gender. Multiply these jobs estimates by the 'vulnerability to automation' coefficients to gain insights about the vulnerability of different states or genders.	See Stage 1 or Stage 3.

Sector study

In addition to making an economy-wide assessment, it would be valuable to NSRD to carry out a sector-specific study (or studies). A strong focus on a particular sector or sectors will further help to understand the changing environment for skills demands and mismatches. In particular, the benefits include:

- The ability to utilise sector-specific knowledge and expertise.
- Being able to identify key stakeholders more easily and bring them together. This gives the opportunity for closer engagement with employers, social partners and other stakeholders than is possible with an economy-wide assessment, though this may be more of a challenge when looking at the informal economy.
- The option of a more comprehensive investigation, focusing on more detailed breakdown of sector-specific occupations and more specific issues facing that sector.
- The possibility to concentrate on skills that aren't as easily quantified (e.g. soft skills, competencies), rather than basing the analysis on more general metrics that can be used across all sectors (e.g. numbers of jobs, formal qualifications).
- The potential to identify changes in job roles and new emerging jobs in the sector.

It is important to note, however, the limitations of conducting several sector studies individually and then combining them to provide an economy-wide overview. The issue with this approach is that there can be a lack of consistency in definitions and underlying assumptions and it can also lead to double counting.

Table 6.2 provides an overview of a methodology NSRD can employ for a sector-specific study.

Table 6.2: Overview of methodology for a sector-specific study

Task	Details
Objectives	**Clarify aims and objectives**
Statement of focus	Develop a clear statement of the objective, rationale and logic of the sector study. It should describe more specifically, what are the policy questions to be answered, who are the relevant stakeholders, and what are their interests in the research.
Defining the sector	Establish a clear definition of the sector to be analysed.
Quantitative analysis	**Create a quantitative sector profile based on statistics**
Carry out a data audit	Research existing available data sources, providing details of each source (e.g. the occupational/geographical/qualification breakdown; time period, etc).
Data collection	This includes collecting data from official statistics and surveys directed at employers (or other groups such as households), containing questions about, for example, employment levels, pay, unfilled vacancies. Use the data to quantify the size and composition of the sector (e.g. how many people are employed in the sector, both now and in the future; how much value added output the sector generates; the characteristics (e.g. age, gender, education-

	level, occupation, location) of people employed in the sector; and the distribution of the size of enterprises in the sector.
Qualitative analysis	**Researched the sector qualitatively to produce a descriptive profile of sector**
Conduct surveys	Carry out a survey of opinion directed at employers (or other groups) containing questions about, for example, skill deficiencies and skill gaps.
Consult key stakeholders	Identify and get on board all relevant stakeholders for the sector (e.g. main employers, main vocational institution, etc). Carry out interviews in order to address problems and concerns more subtly and in greater depth (e.g. the impacts of technological change on certain processes in the sector).
Organise workshops	Bring together key representatives of the sector for workshops, providing a useful mechanism for exchanging views.
Sector outlook	**Provide a description of the vision for the future of the sector.**
Projections	If available, make use of official employment projections for the sector based on a quantitative model, in order to examine the future implications for the number of workers and the types of skills demanded in the sector.
Synthesize analysis	**Bring together the quantitative and qualitative analysis to develop an understanding of the business environment and the sector's place in the current and future environment.**

Skills forecasting

As described in Chapter 2, skills forecasting provides a common and consistent economy-wide overview of skill needs, allowing detailed comparisons across sectors. For the analysis of Industry 4.0, such forecasting models can provide:

- A benchmark against which to compare alternative expectations of the future.
- A systematic framework in which to develop and quantify alternative future scenarios.

Forecasting models typically assume that past relationships and behaviour will persist into the future, and so, they are not very suitable to model scenarios of disruptive events such as Industry 4.0. However, with interventions and adjustments to the models, it can be possible to design alternative future scenarios to characterise developments such as Industry 4.0 (IAB 2016). Such interventions and adjustments to the models need to be informed by well-designed consultations with stakeholders and experts (using *skills foresight* exercises, see below).

We recommend that NSRD engages with the NSDC to find out about the sectoral employment projections that are published in Appendix-I of the National Policy on Skill Development and Entrepreneurship. Find out: what methods were used the derive the projections, are they from skills assessments, skills forecasts or a quantified model[20]; who is responsible for

[20] The National Policy on Skill Development and Entrepreneurship refers to the projections being the result of a 'skill gap study'.

the projections; and is there any commitment to update them (on a regular basis).

We do not at this stage recommend that NSRD develops a skills forecasting model. To do so would be a substantial commitment (and it may be that NSDC has already started to develop such a model) and the other research recommended here is intended to better investigate the impacts of Industry 4.0. Undertaking the recommended research will though gather information and data to better assess the feasibility and efforts required to develop a skills forecasting model for India, to help inform such a decision in the future.

Skills foresight

As described in Chapter 2, skills foresight exercises are a useful approach to skills anticipation. The stakeholder engagement recommended in Stage 3 of the vulnerability to automation analysis is an exercise in skills foresight.

We recommend that NSRD considers other opportunities for skills foresight exercises. Reflect on NSRD's refined rationale for the research and the policy questions to be answered. For example:

- Consider if the stakeholder engagement recommended in Stage 3 could be extended to research any of these questions.
- If NSDC plans to update the 'Industry reports', could they be designed to research the specific impacts of Industry 4.0 (e.g. the impacts on different types of business (size, informal) in a sector).
- If a suitable skills forecasting model already exists, consider using it to develop an Industry 4.0 scenario: design skills foresight exercises to develop the required assumptions (e.g. what will be the scale of investment to facilitate automation, which jobs might benefit and lose from the structural shifts etc).

6.5 Draw policy conclusions from the results

The findings of the research can be used to:

- inform various actors of future labour market needs as an aid to their choices and decision-making, for example
  - education and training providers - capacity and curriculum
  - employers – recruitment and training
  - individuals – careers, education and training
- support policy-making in employment and social protection, education and lifelong learning

From NSRD's refined rationale for the research, identify the relevant stakeholders and their interests in the research. Collate the evidence from the research, map it to and answer NSRD's refined list of policy questions, and draw policy conclusions. Interpret the findings in the given context and conditions, and policy priorities for India. Plan how to disseminate the findings with the relevant stakeholders.

6.6 Summary and next steps

This *Foundation Report* makes recommendations about how the National Skills Research Division (NSRD) should take forward its own research into the potential impacts of Industry 4.0, on the economy, and on current and future skills in India.

NSRD is recommended first to review and refine the statement of the focus, rationale and logic for its research. It should describe more specifically what are the policy questions to be answered, who are the relevant stakeholders, and what are their interests in the research. We recommend that NSRD complete a comprehensive review of datasets to assess if better sources of data for India are available than those than we have identified in a brief review of data. Recommendations are made about how to identify and shortlist the priority sectors, how to analyse the likely impacts, how to engage and involve stakeholders, and how to draw and disseminate policy conclusions from the results.

CE is available to discuss these recommendations with NSRD. The expectation is that NSRD will then take forwards the plan to complete their further research. It is suggested that 2-3 months after the delivery of the report, after NSRD has had chance to progress their research, CE visits NSRD in New Delhi to spend time to give practical advice about any issues arising. The visit may also be an opportunity for CE and NSRD to meet with other stakeholders to gather further evidence for the research, or to further engage and disseminate the research.

Appendices

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Appendix B Questionnaire for evidence review

1) Summary

Title

Author

Weblink to literature

What is the aim of the report/study?

2) Scope

What is the geographically scope of the study?

Does the study look specifically at "Industry 4.0", or other aspects of technological change? How is this defined?

What sectors does it focus on?

What occupations does it focus on?

3) Methods

A summary of the methodology used (if applicable)

What data sources have been used?

What other evidence has been used (e.g. interviews)?

4) Findings

What are the potential impacts of Industry 4.0 on the economy?

What are the potential impacts on current and future employment?

What are the potential impacts on current and future skills?

What are the potential impacts on different parts of the labour force/population (for example, the inactive, the low-skilled, those without formal education)?

What opportunities are identified?

What challenges are identified?

Does the study comment on measures (e.g. policy) to deal with the opportunities and/or challenges?

Are any results specified for India, or are there any results that you think are relevant to India?

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