山东青年政治学院

SHANDONG YOUTH UNIVERSITY OF POLITICAL SCIENCE

学 士 学 位 论 文

技术进步对自动化就业的影响研究

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Research on the impact of technological progress on Automated employment

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Contents

Abstract

In the two centuries since the Industrial Revolution, technological advances have had a major impact on the types of work humans do. The invention of advanced machinery has increased the need for certain forms of manual labor while creating new demands and new types of work. Through the continual cycle of this process, the emergence of advanced industries has enabled the rise of living standards throughout the world. The latest wave of technological progress, characterized by ever-smarter computers and computer-powered machines, has coincided with a rise in economic inequality in previously equal countries, fueling debate about the impact of the computer revolution on low- and middle-skilled workers. In this study, the focus is on the likely impact of these developments on the South African labor market. Future prospects are identified and presented using computerized probabilities from Frey and Osborne (2013) combined with Stats SA labor market data (what year?). The findings suggest that nearly 35 percent of South African workers, or about 4.5 million people, are employed in occupations that are likely to be automated in the near future.

Key words: Computerisation; Labour; South Africa

CHAPTER 1

INTRODUCTION

Based on a report by Oxford Economics, the robotics revolution is rapidly accelerating with rapid advances in technologies such as automation, engineering, energy storage, artificial intelligence and machine learning. The far-reaching results will change the capabilities of robots and their ability to take over tasks once performed by humans. Existing business models across many industries will be severely disrupted and millions of existing jobs will be lost. We estimate that up to 20 million manufacturing jobs will be lost to robots by 2030

With few exceptions, Luddism lost steam as productivity gains from technological progress created new jobs for unemployed workers. This process continued throughout the 19th and 20th centuries, resulting in increasing productivity and living standards (Rifkin, 1995; Brynjolfsson and McAfee, 2012, 2014). More recently, however, experts have reignited Luddite fears that, unlike machines built to save physical labor, modern digital technologies have the power to replace cognitive labor. It has been argued that this new wave of technological revolution has the potential to alter the relationship between labor and capital in unprecedented ways (Brynjolfsson and McAfee, 2012, 2014; Rifkin, 1995; Marchant et al., 2014; Naude and Nagler, 2015)

Importantly, modern Luddism appears to reflects 'an anti-inequality ideology' (Lehman, 2015, 266) rather, not to be 'overtly antitechnology or antimachine per se' but reflects,. Central to this standpoint are two key arguments. The first requires technological advances to create a skills bias in the economy that risks triggering long-term structural unemployment. Second, such biases devalue low-skilled labor, thereby increasing economic inequality and leading to the hollowing out of the middle class Lehman (2015). While the debate about the validity of modern Luddite claims is intense, some publications on the subject (Sabadash, 2013; Brynjolfsson and McAfee, 2012, 2014; Rifkin, 1995) have begun to gain mainstream economics recognized by experts (Naude and Nagler, 2015)).

Research in this area has been dominated by academics and statistics from technologically mature countries in the developed world, and perhaps unsurprisingly, little attention has been paid to the fate of developing countries. The research aims to address this gap in the literature by investigating the possible impact of advancing computer technology on the South African labor market. To this end, two main research objectives were addressed:

1. Determine the range of occupations in which South African workers work based on publicly available data and estimate the number of workers in each occupation.

2. To determine, based on the findings of the first objective and Frey and Osborne (2013)'s computerisation probability index, how advancing automation technologies may affect labour demand in South Africa.

Three factors make South Africa an interesting case for the analysis of automation and labour demand. The first is that, due to its history of colonization and apartheid, it has become one of the most unequal economies in the world (World Bank, 2016; Van der Berg, 2011). The second, closely related to the first, is its high unemployment rate (24.9%) (World Bank, 2016). The third is that, while South Africa is a developing nation, it has, by global standards, some technologically- advanced industries. The financial sector is a typical example. South Africa is ranked 8th (out of 140 countries) in Financial Sector Development from the record of the 2015/2016 World Economic Fo-rum Global Competitiveness Survey.

The article begins with an overview of the discourse on technology and employment, briefly summarizing key insights from this field of study. What follows is an overview of the South African economy based on World Bank data. Using labor force data collected by Statistics South Africa (StatsSA), combined with Frey and Osborne (2013) projections of job susceptibility to computerization, the study examines the likely impact of advanced computing technologies on the South African labor market.

It is important to note that the author adopts an amoral stance on the matter under investigation. No agenda, be it pro- or anti-technology, egalitarian or capitalist is favoured.Rather, the interest lies in an unbiased analysis of the various positions taken by a range of scholars and a balanced introduction to South African labor dynamics. While acknowledging the importance of the moral and ethical dimensions of the discourse, it is beyond the scope of this article to assume these.

CHAPTER 2

The relationship between technology and employment

It is broadly acknowledged that the dynamic nature of technological innovations negates our ability to accurately predict the Future impact of any given technology on labor demand (Sabadash, 2013). This applies in particular to information technology (IT), which firstly affects labor demand in different ways across industries and sectors (Sabadash, 2013; Brynjolfsson and McAfee, 2012), and secondly, capacity and application areas continue to grow rapidly. There are many competing perspectives being discussed, promoting different interpretations of economic indicators such as GDP, median income, unemployment rate, and economic inequality.

One idea, which has been gaining interest in the United States since the mid-1990s, is that we are approaching a new era in which the need for human labor will decrease. It builds on the work of Rifkin (1995) and provides a compelling rationale for recent economic trends in the United States of America (US) (Brynjolfsson and McAfee, 2012, 2014; Rifkin, 1995).

According to Rifkin, the concept of continuous technological change or technological progress has been a key driver of capitalist economies. Schumpeter's concept of "creative destruction" describes this feature of capitalism well - continuous cycles of the destruction and renewal of economic structures (Naude and Nagler, 2015; Sabadash, 2013; Frey and Osborne, 2013; Collins, 2010). In this case, technological progress is not limited to the development of the technology industry. While these developments play an important role, the development of machinery or other technological artifacts is only one aspect of creative destruction.Cragg's (1963) knowledge-centred definition of technological progress illustrates this point: "Technical progress consists of the acquisition of new knowledge that enhances the economy's ability to meet economic needs and the ease with which it is used" (Cragg, 1963, 312). Technological progress may thus occur without new or updated artefacts, for example, when new knowledge enables a production company to improve quality by adopting new production processes while using the same production equipment and labor Enter efficiency.

2.1 Technological Progress and Productivity

One of the main feature of technological progress is its impact on productivity. Productivity can be defined as the increased output achieved per unit of labour input, generally indicated, on macro level, as an increase in Gross Domestic Product per capita. Research conducted in multiple industries over the past two centuries has consistently found that technological advances increase productivity (Cragg, 1963; Brandtzaeg, 1979; Brynjolfsson and McAfee, 2014, 2012; Collins, 2010; Lehman, 2015; Frey and Osborne, 2013; Haber and Kahn, 1957; Marchant et al., 2014; Rifkin, 1995; Sargent, 2000; Sabadash, 2013).

Rifkin (1995) provides striking historical statistics on the impact of this relationship on the US agricultural sector. In 1850, one farm worker produced enough food to feed four people. However, by 1995, one farmer was producing enough to feed more than 78 people. The first mechanical cotton pickers, introduced in the Mississippi Delta in 1944, picked 1,000 pounds of cotton in one hour, the equivalent of 50 experienced hand pickers. The technology's initial adoption was rather slow—by 1949, only 6 percent of the cotton in the southern United States was harvested mechanically, but by 1964 that had grown to 78 percent. By 1972, the hand-picked cotton service was out of service. In 1995, less than three percent of the American workforces were engaged directly in farming, down from 60% in 1850 (Rifkin, 1995)

These historical trends are not limited to agriculture. In the decade between 1980 and 1990, U.S. Steel shrunk its workforce from 120,000 to 20,000 while production remained roughly constant, supported by increasingly sophisticated equipment (Rifkin, 1995)

Statistics such as these are prevalent in labor-intensive industries, where the constant introduction of new technologies has enabled businesses to achieve significant increases in productivity. Collectively, these gains have contributed to the sustained rise in median income and quality of life observed globally over the past two centuries (Sabadash, 2013).

More recently, advances in IT have begun to bring about similar productivity gains in white-collar occupations. In office settings, the application of computing machines has increased the efficiency and quality of tasks that require cognitive rather than physical input from human workers (Frey and Os-borne, 2013). This new wave of technological advancement is systematically entering areas of work hitherto reserved exclusively for human workers (Brynjolfsson and McAfee, 2014, 2012; Rifkin, 1995).On the one hand, advances in artificial intelligence and machine learning tend to gather a lot of media attention—Google’s self-driving cars and IBM’s Watson are prime examples. Less well-known, however, are the incremental advances made by global hardware and software producers, which are embedded in companies across a wide range of industries and impact their operations, structure, and workforce needs in a variety of ways.

2.1 Technological Displacement of Human labor

Technological substitution of jobs is when the need for human labor in certain occupations is reduced or eliminated due to technological advancement. As mentioned earlier, this has been a consistent feature of capitalist development for over 200 years. Yet despite this displacement, employment has remained relatively stable. This is possible because while certain types of jobs are destroyed, the introduction of technology also creates new labor demands. If a balance is maintained between the destruction and creation of demand for human labor, employment levels will not be disturbed by technological progress.

Labor market data suggest that over the past two centuries, the job-creating effects of technological advances have offset their job-destroying effects (Brynjolfsson and McAfee, 2012), at least if data from “healthy economies” are considered (Harford), 2012). This is evident in the combined rise in productivity and median household income. Over the past 15 years, however, these two indicators have begun to break this pattern in the US and Europe. In the US, GDP per capita "continues to grow fairly steadily (except during recessions)", but median household income has not followed suit, and since the turn of the century it has begun to decline steadily (Brynjolfsson and McAfee, 2012, 33) .This paradox of achieving sustained productivity growth without increasing median income, often referred to as unemployment growth, is at the heart of contemporary Lutheranism. In this case, the winners are the capitalists who own and control the machines of production, while low-skilled (and more recently semi-skilled) workers are driven out due to the devaluation of labor. This phenomenon breaks the traditional “bargaining principle between capital and labor”, as “the share of income earned by equipment owners” has increased relative to that earned by workers (Brynjolfsson and McAfee, 2012, page 45).

2.2 Technological Skill-Biased Concept

An important feature of technological progress is its preference for skills. It increases labor market demand for some skills while reducing demand for others. For example, the introduction of mechanical cotton pickers reduced the need for manual cotton picking skills but increased the need for skills related to the development, production, operation and maintenance of mechanical cotton pickers.

In the same way, the computerization of white-collar work will reduce the need for skills related to routine or rule-based tasks in the office environment (Frey and Osborne, 2013). Administrative functions such as data processing and bookkeeping are typical examples, but with the development of robotics and numerically controlled machinery, the scope of automated work has inevitably expanded. Skills that are in increased demand are more advanced, technology-oriented skills related to the design, development and maintenance of hardware and software. As the demand for these skills increases, so does the compensation of suitably skilled workers, especially when their skills are scarce.The ensuing pattern implies that high-skilled workers reap the benefits of automation while the demand for and remuneration of low- skilled workers decrease.

There are two important features of this phenomenon that deserve emphasis. The first is that increasingly intelligent machines increase the skill levels required by human workers to remain relevant in the labor market. A natural consequence of this is an increased demand for higher education, which is particularly evident in the current South African context. However, a second feature, as shown in the analysis of US labor force statistics by Brynjolfsson and McAfee (2012), is that the demand for high-skilled labor has not grown at the same rate as the demand for low-skilled labor has contracted.

This trend suggests that firms can achieve the same productivity levels while shrinking their overall work forces. Of course, the specialised skills that they require to manage

advanced technologies come at a premium. So even though the company's net profits may not increase, those profits will go to a small group of high-skilled workers, while their low-skilled colleagues are on the loose. The resulting macro-level impact has been lower median incomes and higher economic inequality (Rifkin, 1995; Brynjolfsson and McAfee, 2012, 2014).

2.3 Competing Perspectives

Opponents of the end-of-job perspective typically take one of two positions: cyclical or stagnant (Brynjolfsson and McAfee, 2012). The cyclical view is that median incomes have failed to rise because the economy hasn't grown fast enough to lead to high unemployment. "In a cyclical interpretation, a large drop in demand like the Great Recession would necessarily be followed by a long and frustratingly slow recovery," implying that the current situation is nothing more than an "on-going business cycle" (Brynjolfsson and McAfee , 2012,4).

Proponents of the cyclical view generally adopt a stance of technological optimism rooted in historical evidence of the long-term positive impact of technological progress. Mokyr et al. (2015) express this point well:

> ‘From our perspective, modern man's anxieties about long-term, ineradicable technological unemployment or a general lack of meaning due to changing patterns of work seem unlikely. As has been the case for more than two centuries, technological advances will continue to improve living standards in many dramatic and unforeseen ways. However, basic economic principles will continue to operate. Scarcity will still be with us, especially time itself. The law of comparative advantage strongly suggests that even in an economy with dramatically increased robotics and automation capabilities, most workers will still have useful tasks to do’.

The stagnant view that has developed around the work of Cowen (2011) argues that the decline in median income is due not to technological progress but to the lack of technological progress. He argues that since the 1970s, the U.S. economy has been on a “technological plateau” characterized by a lack of powerful new ideas to drive economic progress (Cowen, 2011). The antidote is seen as more and faster technological progress to increase productivity, which in turn creates jobs that will lead to a rise in median income. Of course, this view contradicts the view that work is over and sees technology as a savior, not a culprit.

Brynjolfsson and McAfee (2012) rejected this proposal. “We think this is because the pace of [technological innovation] has accelerated so much that many people are being left behind. In short, many workers are racing against the machines” (Brynjolfsson and McAfee, 2012, p. 8) . Furthermore, they argue that "technological advances—particularly improvements in computer hardware, software, and networking—are so rapid and surprising that many of today's organizations, institutions, policies, and ways of thinking cannot keep up"(Brynjolsson and McAfee, 2012, 8).

2.4 Social Shaping Factor of Technology

It is important to acknowledge that accurate predictions of technological development and innovation outcomes are hampered by the way a range of socioeconomic factors affect these processes. Williams and Edge (1996) describe this perspective as the social shaping of technology (SST), which facilitates critical engagement with these factors, and frames technological innovation as a "garden of forking paths", the direction or trajectory of which is determined by multiple Selection decisions are made by multiple actors (Williams and Edge, 1996). SST contrasts ideas about technological innovations as linear, predictable processes as promoted by technological determinism. Instead, it recognizes the role of human labors and their choices in determining how the development, diffusion, and adoption of technologies occur. This includes the ways in which technology developers' world views are embedded as "latent structures" (Strong and Volkoff, 2010) in the artifacts they produce; the processes by which technologies are disseminated and adopted by individuals and organizations (Rogers, 2003); and The non-linear way in which users understand and implement their functional visibility (Orlikowski and Gash, 1993; Le Roux, 2013).

In the context of this study, SST notes that the design, diffusion, and implementation of labor-saving or replacement technologies are complex, unpredictable processes. Treating them as linear and predictable will inevitably lead to wrong assumptions and conclusions. This raises the question of whether there is any value in forecasting the impact of technological advances on labor demand. Cilliers (2000) provides a clear perspective on this issue, arguing that models of complex systems can be valuable despite their limitations. “We must do all the calculations that we can. This is our first responsibility as scientists and managers. Computing and modeling will provide us with a lot of important information. It will not provide us with all the information” (Cilliers, 2000). Thus, this study takes the view that while technologies are socially shaped and their effects on social systems cannot be accurately predicted, some value can be derived from efforts to determine these effects based on models and calculations (as this study does like that)).

CHAPTER 3

A BRIEF OVERVIEW OF SOUTH AFRICAN ECONOMIC INDICATORS

Two aspects of the South African economy generally dominate mainstream discourse. First, there has been a lack of recent growth, and second, there is high economic inequality among South African citizens (which is reflected and exacerbated by high unemployment).

The World Bank reports that South Africa's GDP in 2015 was about $313 billion. According to 2015 data, services accounted for 67.4% of the country's GDP, while industry accounted for 30.3% and agriculture 2.4% (CIA, 2016). While GDP growth has risen steadily since the 1980s and initially recovered well after the Great Recession (2007-2009), it dipped below 2.5% in 2012/2013 and below 2% in the two years since. This lackluster growth meant that South Africa’s GDP shrank by about $60 billion in dollar terms between 2010 and 2015.

Over the same period, the labor force has grown from about 18 million to about 20 million (the 30th largest in the world), and unemployment has hovered around 25%. It reached $5,691 in 2010 and 7 in 2015. Term (208 countries) South Africa ranks 31st for GDP size, 162nd for GDP growth, 118th for GDP per capita and 180th for employment.

South Africa: Gross domestic product (GDP) in current prices from 1987 to 2017

While South Africa is not the only economy struggling to grow after the recession, its high levels of inequality make it stand out among comparable cases. Inequality is a sensitive subject in the country's public discourse, indisputably tied to its history of apartheid. “In South Africa, where racial inequality is high, inequality in income distribution is particularly high and persistent. For upper-middle-income countries (in terms of GDP per capita and economic structure), South Africa’s social indicators (for example, life expectancy, infant mortality, or education quality) closer to that of low-middle-income or even low-income countries (Van der Berg, 2011, 120).

However, Van der Berg (2011) cautions that one should be cautious about taking an overly simplistic view of the sources of inequality. "Racial discrimination, especially apartheid, is widely blamed for inequality and even poverty in South Africa. This of course provides only a partial explanation. Colonial settlement and subsequent mineral discoveries set the stage for a highly dual economy in a poor pre-colonial society. The foundations of this economy were highly egalitarian from the outset. First racial discrimination under British colonial rule, then apartheid, which divided the spoils of economic growth by race, laid the groundwork for the further development of a racially stratified society and a pattern of privilege foundation” (Van der Berg, 2011, p. 120).

As noted in the previous section, it is impossible to determine precisely the extent to which job automation has affected income inequality in South Africa over the past century. However, it is well known that racial discrimination negatively affects the availability and quality of education for disadvantaged groups (Van der Berg, 2011, 134). On this basis, one could argue that workers from these groups are more vulnerable to technological substitution than highly skilled workers from privileged groups. Such an argument acknowledges the role of technology in maintaining economic inequality by affecting labor demand, opposing Friedman's (2007) view that technology is a flattener or equalizer of the economic playing field.

Indicators for South Africa provide little evidence of economic growth, thus negating the assumption that the pattern of unemployment growth observed in the United States is also currently occurring in the United States. Furthermore, any comparison between the two economies should be made sensitively to the vastly different levels of technological (and, by implication, knowledge) maturity in their industries. However, that doesn't mean South African workers are immune to the wave of automation currently permeating U.S. companies. As these technologies mature and become less expensive, they will become increasingly attractive to companies in developing economies. From an SST perspective, one should be mindful of the impact of the availability of cheap labor on the adoption of automation. Capitalist owners will compare the costs of technologies to those of human labour when considering adoption and it may not be cost-effective to automate (yet). However, labour-related factors like wage increase demands, strikes and unionisation may make automation an attractive strategy despite higher costs.

CHAPTER 4

RESEARCH DESIGN

This study set out to determine the possible future impacts of the adoption of increasingly advanced computing technologies for labour demand in South Africa.

To address this question, we analyzed two data sources. The first is data describing the current structure of South Africa's labor force according to the type of work people do. Statistics South Africa (Stats SA) conducts the Quarterly Labor Force Survey (QLFS), a household sample survey that collects “data on labor market activity among individuals aged 15 and over” residing in the country. The survey covers a large number of variables, including respondents' current occupation and industry. In their analysis, the researchers utilized the South African Labor Market Dynamics (LMDSA) dataset (2012-2019), which was constructed using data from four QLFS datasets per year.

A second source is the Occupational Computerization Probability Index developed by Frey and Osborne (2013) of the Oxford Martin Institute for Future Technology Impact. In their oft-cited study, the authors analyzed 702 occupations as defined by the U.S. Department of Labor with the goal of determining the likelihood that jobs in each occupation could be computerized. The authors' analysis is based on a model that considers the existence of three types of tasks in occupations: perception and manipulation tasks, creative intelligence tasks, and finally social intelligence tasks. Based on these factors, they follow a multi-step process to generate probabilities

1) For each occupation.

In a subsequent analysis of the U.S. labor market, they concluded that "approximately 47 percent of total U.S. employment" is likely to be computerized "relatively soon, perhaps within the next decade or two" (Frey and Osborne, year 2013). “Most workers in transportation and logistics industries, as well as a large proportion of office and administrative support staff, and the workforce in production industries are at risk of automation” (Frey and Osborne, 2013).

The list of occupations analysed in the automation index is based on US Labour Department’s Standard Occupation Classification (SOC). Stats SA, however, utilises its own classification system in the QLFS The South African Standard Classification of Occupations (SASCO). For compatibility between datasets, researchers manually matched SASCO occupations with their SOC correspondents. In most cases, occupations can be matched with a high degree of confidence based on names used in different systems. However, when this was not the case, the researchers consulted SOC and SASCO descriptions to find correspondents.

According to the LMDSA dataset, South Africans worked in a total of 377 different occupation types in 2019. The researchers were able to match 285 of these with corresponding SOC occupations and thus computerized probabilities. SASCO occupations that cannot be linked to their SOC counterparts usually have a small number of workers. These include, for example, traditional chiefs and village heads; subsistence farmers; mining and quarrying workers; and faith healers.

Combined, these occupations accounted for less than seven percent of the employed workforce in 2014.

Having established compatibility between the datasets, the researcher analysed the data in two primary phases. The first phase involved a high-level analysis of trends in the period between 2012 and 2019. This afforded the researcher an overview of the labour market structure and the identification of growing and declining occupations during this period. Of course, the Great Recession falls within the period analysed and its implications for the labour market are reflected in the data.

The second phase of the analysis considered the future implications of the computerisation of work by relating Frey and Osborne (2013)'s probabilities to the labour market structure as represented by 2019 LMDSA data. This included the stratification of the labour market data based on population groups (African/Black; Coloured; Indian/Asian; White).

CHAPTER 5

FINDINGS

Before considering labor market trends from 2012 to 2019, it is worth noting some general data describing the South African labor force. According to the World Bank, South Africa's working-age population (all people aged 15-65) accounts for about 65% of the total population (approximately 35 million people). The labour force, which neither excludes those persons who are not employed nor seeking employment consists of roughly 20 million people. Of those 20 million people, about 12 million were employed and paid in 2019.

Among these earners, the top 10 percent accounted for more than 50 percent of total income, while the top 20 percent accounted for almost 70 percent. Because of this uneven distribution, it is estimated that only about 3.3 million workers pay 99 percent of all income tax collected by the South African Revenue Service (SARS) (Joubert, 2013).

5.1 General Trends (2012 to2019)

In each of the six LMDSA datasets covering the period between 2012 and 2019, an average of around 40% of people aged 15-65 are associated with specific occupations. Consequently, the analysed section of the sample for each year ranges between just over 13 million people (2012) to just over 14 million people (2019).

According to 2019 figures over half of all South African workers (7.08 million people) perform just 20 different occupations. These occupations are shown in Table 1. The table shows occupations, the number of workers in 2012 and 2019, and changes in these numbers over the relevant periods. It should be noted that comparison of the LMDSA data across years suggests that certain changes in data coding practices were implemented. For example, as shown in the table, the data shows a sharp decline in the number of street food vendors, but a significant increase in the number of chefs.

This figure is higher than the number of workers claiming to be in paid work, suggesting that many workers are classified in occupations that do not necessarily receive remuneration. For example, based on 2019 data, just over 7% of people claiming not to have paid work own businesses.

Table 1: The 20 largest occupations and their growth/declined between 2012 and 2019

Occupation	2012	2019	Change	% Change
Domestic helpers and cleaners	1 075 993	1 030 588	-45 405	-4%
Farmhands and labourers	834 886	905 965	71 079	9%
Other office clerks and clerks not elsewhere classified ...	373 351	521 360	148 009	40%
Helpers and cleaners in offices, hotels and other...	475 298	511 056	35 758	8%
Shop salespersons and demonstrators, Salespersons ...	393 841	455 255	61 413	16%
Police officers, traffic officers, Police officers	127 190	173 709	46 519	37%
Finance and administration managers/department managers	137 795	172 019	34 225	25%
Protective services workers not elsewhere classified ...	346 118	438 888	92 770	27%
Hand-packers and other manufacturing labourers	396 023	396 684	661	0%
Street vendors, non-food products	143 638	160 110	16 472	11%
Street food vendors and related workers	437 589	317 885	-119 704	-27%
Cashiers and ticket clerks	260 218	285 530	25 312	10%
Primary education teaching associate	282 719	268 257	-14 463	-5%
Professionals Cooks	172 314	264 491	92 177	53%
Motor vehicle mechanics and fitters	193 122	173 350	-19 772	-10%
Bricklayers and stonemasons (including apprentices/trainees)	275 735	225 366	-50 369	-18%
Heavy truck and lorry drivers	210 677	215 692	5 015	2%
Sweepers and related labourers	45 688	205 293	159 605	349%
Teaching associate professionals not elsewhere classified	233 046	190 313	-42 732	-18%
Construction and maintenance labourers: roads, dams ...	207 132	176 711	-30 420	-15%
	6 622 371	7 088 521		

The outlier in the table is sweepers and related labor, which increased by 349% over the relevant period. Bhorat et al. (2016) argued that this could contribute to the government's Extended Public Works Program (EPWP). ‘The EPWP creates jobs through government funded infrastructure projects, through its non-profit organization and community work programme, as well as through its public environment and culture programmes. Consequently, most of the employment growth in the public sector...is related to the construction, protection and safety sectors, public health and personal care industries” (Bhorat et al., 2016, 20).

A short analysis on IT-oriented occupations reveals some interesting trends (see Table??). Perhaps most interesting is that there were an estimated 3 689 fewer Computer Programmers in 2019 than in 2012 (a drop from 21 211 to 17 522). However, Computer systems designers and analysts grew from 22 796 in 2012 to 31 783 in 2019, an increase of 8 987 workers. Similarly, Computing services managers/department managers grew from1334to9221overtherelevantperiod.[4]Computer assistants increased by 4905 while Electronics and telecommunications engineers dropped from 3 473 in 2012 to 2691 in 2019.

Of course, these figures are not necessarily reflective of changes in demand for IT skills. Outsourcing or offshoring of jobs and immigration of highly skilled IT workers are examples of factors that may contribute to changes in the number of IT professionals in South Africa.

Analysis of administrative white-collar occupations also reveals some interesting trends. One occupation which has grown quite substantially (40%) is Office clerks and clerks not elsewhere classified. Closer inspection of the data suggests that this growth can largely be attributed to government and government-owned organisations, with little change observed for private sector organisations. Overall, public sector employment has grown from 14.5% of total employment in 2012 to 17.5% in 2019, creating more than half a million jobs during a period of ‘extreme labour market distress’ (Bhorat et al., 2016).

While high-skilled and middle-skilled occupations such as accountants and bookkeepers have increased, it is clear that most low-skilled administrative occupations are shrinking. Accounting and bookkeeping clerks dropped by 12 469 while Library and filing clerks dropped by 41 303. So too has Receptionists and information clerks (-19%), Secretaries (-9%) and Stock clerks(-9%).

Of course, these figures do not provide concrete evidence that technology is affecting labor demand. Occupational growth and decline can be caused by a variety of factors, and to isolate the effects of technological progress across sectors and industries, one needs to consider evidence on firm/industry level technology capital investment (to the best of the researchers' knowledge, this is not publicly available at present) Associated with career growth and decline.This increase in occupational size (591%) may again lead to changes in coding practices related to QLFS. It may also be due to the lack of texture in the IT occupation types on the SASCO list, which represents an increasingly broad range of professional roles.)

Table 2: Workers in administrative office occupations from 2012 to 2019

Occupation	2012	2019	Change	% Change
Other office clerks and clerks not elsewhere classified...	373 351	521 360	148 009	40%
Accountants and related accounting occupations	68 271	72 509	4 238	6%
Administrative secretaries and related associate professionals	10 342	11 466	1 124	11%
Bookkeepers	34 043	34 684	641	2%
Statistical finance clerks	57 541	56 714	-827	-1%
Secretaries	80 650	73 646	-7 004	-9%
Accounting and bookkeeping clerks	65 594	53 098	-12 496	-19%
Stock clerks	142 799	130 024	-12 774	-9%
Receptionists and information clerks	108 768	93 303	-15 465	-14%
Library and filing clerks	68 261	26 958	-41 303	-61%
Data entry operators	31 691	31 765	74	0%
Word-processor and related operators	3 426	2 646	-780	-23%

Table 3: Estimated number of occupants at risk levels 1 to 10

Risk level	Probability range	Number of workers
1	0-0.099	1 975 149
2	0.1-0.199	717 199
3	0.2-0.299	311 022
4	0.3-0.399	621 955
5	0.4-0.499	65 028
6	0.5-0.599	316 779
7	0.6-0.699	1 909 588
8	0.7-0.799	1 093 360
9	0.8-0.899	2 605 365
10	0.9-0.999	3 613 811
Total		13 229 255

5.2 Risk of Computerisation

By combining Frey and Osborne (2013)'s probabilities with the 2019 LMDSA data, it is possible to produce an estimation of the implications of advancements in computing technologies .The readers should interpret such estimation with the understanding that the probabilities reflect Frey and Osborne (2013)'s predictions of which occupations could, through advances in machine learning and robotics, be computerised rather than actual changes in labour demand. There are significant differences between the availability of a technology, its commercialisation, its uptake and, finally, its impact on labour demand. Nonetheless, historical examples (e.g., the mechanical cotton picker) provide strong evidence that labour-saving technologies can infiltrate industries rapidly once their benefits outweigh their costs.

Based on 2019 data, the 285 occupations analyzed in this section (i.e., occupations related to the probability of computerization) represent approximately 13.2 million South African workers. For analytical purposes, the researchers classified occupations into 10 risk classes based on the Frey and Osborne (2013) probability.The highest risk category (10) represents occupations with a probability of 0.9 or much higher, while the lowest risk category (1) represents occupations with a probability of less than 0.1. Table 3 lists the 10 risk categories and the total number of workers in each category based on 2019 data.The distribution is visualised as an area graph in Figure1.

Level 10, indicating a very high likelihood of computerization, includes 64 occupations. These 64 occupations represent an estimated total of over 3.6 million workers (27.3% of the total workforce). Just over 520 000 workers at this level are employed as general Office clerks and another 450 000 as Shop salespersons and demonstrators, Salespersons, Petrol pump attendants.Total employment in these occupations increased by about 340,000 between 2012 and 2019.

From level 9, which includes 39 occupations, represents nearly 2.6 million people (19.7% of working force).Farmhands and labourers represent just over 900 000 workers at this level and the level grew by around 77 000 workers between 2012 and 2019. Level 8 (29 occupations, 1.1 million workers) grew by 112 000 workers in the analysed period, while level 7 (17 occupations, 1.9 million workers) grew by roughly 43 000 workers.

Computerisation risk level

Figure 1: Area graph showing number of workers (vertical axis) versus computerization risk level (horizontal axis).

1 million of the Level 7 workers represents domestic helpers and cleaners. Levels 7 to 10 combined include more than 9 million (nearly 70%) South African workers.

Levels 4, 5 and 6 together represent 34 occupations and just over 1 million workers,declining by around 30 000 workers in the seven year period analysed. Almost 400 000 of these workers are employed as Hand-packers and other manufacturing labourers, which has a computerisation probability of 0.38.

Level 1 occupations (65 total), the most computerization-resistant occupations, represented nearly 2 million people. A large number of occupations at this level include primary education teaching professionals (268 257), police and traffic officials (173 709) and nurses (143 014). On average, Tier 1 occupations represent employment of just over 30,000 people per occupation, well below the average of around 70,000 observed at Tier 10. The occupation at this level added 270,000 workers between 2012 and 2019.

5.1 Risk of Computerisation and Population Groups

Statistics from SA distinguishes four demographic groups: Black/African (80.2% of the population), People of Color (8.8%), Indian (2.5%) and White (8.4%). According to 2019 LMDSA data, about 31 percent of black people ages 16 to 65 have paid employment. This percentage is slightly higher among people of color (45%) and Indians (42%), but similar to whites (34%). However, only 4.5 percent of whites were considered unemployed (not employed but looking for work), compared with 23.7 percent of blacks. 17% of people of color and 9% of Indians are unemployed.

Around 71% of workers in the ten risk levels that were analysed are black (9.38 million), 14% are coloured (1.86 million), 12% are white (1.58 million) and 3% are Indian (400 000). Table 4 presents a breakdown of workers in the four population groups based on the 10 risk levels.

Table 4: Estimated number of occupants by risk levels and population group

Risk level	Black	Coloured	Indian	White	Total
1	1 166 658	241 847	88 251	478 393	1 975 149
2	333 165	87 039	48 292	248 704	717 199
3	150 611	45 234	23 806	91 371	311 022
4	442 731	124 761	10 713	43 750	621 955
5	35 418	12 247	2 891	14 471	65 028
6	221 117	40 172	12 413	43 077	316 779
7	1 599 458	259 156	14 964	36 010	1 909 588
8	750 573	182 079	33 158	127 549	1 093 360
9	2 086 379	380 978	34 858	103 150	2 605 365
10	2 595 975	489 409	134 843	393 585	3 613 811
Total	9 382 085	1 862 921	404 187	1 580 061	13 229 255

Table 4: Estimated number of occupants by risk levels and population group

Risk level	Black	Coloured	Indian	White	Total
1	12,4	13,0	21,8	30,3	14,9
2	3,6	4,7	11,9	15,7	5,4
3	1,6	2,4	5,9	5,8	2,4
4	4,7	6,7	2,7	2,8	4,7
5	0,4	0,7	0,7	0,9	0,5
6	2,4	2,2	3,1	2,7	2,4
7	17,0	13,9	3,7	2,3	14,4
8	8,0	9,8	8,2	8,1	8,3
9	22,2	20,5	8,6	6,5	19,7
10	27,7	26,3	33,4	24,9	27,3
	100,0	100,0	100,0	100,0	100,0

It is clear from the data that previously disadvantaged demographic groups are more likely to be unemployed than white groups due to the computerization of work. 75% of black workers are on a grade 7 to 10, as are 70% of workers of color. For all groups except whites, the largest fraction of workers are at level 10. However, for whites, the largest portion is at level 1 (over 30%). The area chart in Figure 2 illustrates these differences. Each graph represents the number of workers in the population (vertical axis) versus their risk level (horizontal axis).

The relatively small number of white workers in high-risk occupations seems to suggest that whites do not experience a significant decline in labor demand due to computerization compared with other groups. While this inference is valid, it should be noted that occupations in the administrative services sector have a large number of white workers. Of the seven occupations with the largest white populations, four are at level 10 (office clerk, salesperson, secretary and accountant) and one is at level 8 (finance and administrative manager). Together, these five occupations employ more than 300,000 of the 1.58 million white workers.

As shown in the area chart for black workers, a large number of domestic helpers and cleaners (over 900,000 black workers in this occupation) caused a spike at level 7. The same pattern can be observed with workers of color. Both groups also have a large number of workers employed as farm workers and labourers, with a computerized probability of 0.97. The excess unemployed, low-skilled workers has kept wages for farm workers low, a situation which culminated in protests and strike actionduring 2012 and 2013.

Africans also fall into the high-risk category, and there is clear evidence that white workers are disproportionately employed in lower-risk occupations. Many questions arise regarding the interpretation of these findings.

The most important relates, firstly, to the accuracy of Frey and Osborne (2013)'s computerisation probabilities and, secondly, how these should be interpreted for a developing country like South Africa. For example, one needs to consider whether there is really a 0.87

probability that the jobs of farm workers and laborers can be computerized, and if so, whether South African farmers will replace their workers with relevant technology.

To address the first question, it is instructive to consider a growing number of emerging technologies that challenge common perceptions of computing capabilities. In 2005, Levy and Murnane (2005) notoriously stated that "so many factors are involved in making a left turn to oncoming traffic that it is inconceivable to discover a set of rules that can replicate driver behavior". Of course, only six years later, Google’s fully autonomous Toyota Prius was released (Frey and Osborne, 2013). Frey and Osborne's (2013) probabilities for certain occupations may in similar fashion be considered far-fetched or overly technically optimistic. Ultimately, only time will tell how far the potential of AI and robotics can extend, and whether the resulting technology can be produced on a sufficiently large scale. In the absence of certainty in this regard, it may be insightful to consider the views of high-tech entrepreneurs such as Mark Zuckerberg, Ray Kurzweil, and Elon Musk, which suggest that we tend to underestimate and Not to overestimate the rate of progress.

To address questions about the diffusion of new technologies, historical cases cited by Rifkin (1995) provide some guidance. To maintain the financial viability of their operations, capital owners must constantly weigh the potential benefits of new technologies against the costs and compare them to the performance of manual labour. If they fail to take advantage of the productivity advantages that automation brings, they risk losing their market position. This is especially true in global markets, where competition is not limited by national borders and therefore access to technology. Of course, governments can take steps to limit technology adoption. For example, promoting the use of manual labor rather than machine labor through subsidies will affect the investment decisions and technology strategies of capital owners. However, as Van der Berg (2011) warns, "direct interventions that artificially alter labor market outcomes without improving education have little prospect of improving poverty and performance, with every possible side effect".

There is broad consensus even among modern Luddites that denigrating or even hindering technological progress is not a viable strategy for economic growth. One solution that has received attention is a negative tax on manual labor Brynjolfsson and McAfee (2012). Another is the concept of Universal Basic Income (UBI). Rifkin cites the work of Robert Theobald, arguing that "as machines do more and more work, humans need a guaranteed income, independent of employment in the formal economy, if they are to survive and the economy is to generate enough purchasing power to buy goods in production and service". He further writes that this would fulfill "the fundamental philosophical belief throughout human history that each individual is entitled to a minimum share of social production" (Rifkin, 1995).

Significantly improving the education system is clearly a key issue for South Africa, which has a large number of low-skilled workers. Growth in teaching and related occupations is evidence that the government is trying to improve in this area. However, Van der Berg (2011) is skeptical that this ideal can be achieved, and concludes that failure to do so hinders any efforts to address poverty and inequality. Furthermore, based on the findings of this study, it has been suggested that technology adoption may reduce the demand for low- and medium-skilled labor in private sector industries, thereby further forcing the government to expand its already bloated public sector employment programme.

While the findings discussed here paint a rather gloomy picture, it is important to also highlight the opportunities created by smart computing technologies. Brynjolfsson and McAfee (2012) call on entrepreneurs to consider the possibility of racing against machines rather than against them. This view, they argue, could lead to "new business models that create value by combining growing numbers of middle-skilled workers with cheaper and cheaper technology." This approach upends the dominant notion of modern tech startups that value is created (and owned) by a small number of highly skilled workers. Perhaps the glaring inequality among its citizens helps inspire South Africa's budding tech entrepreneurs to rise to the challenge.

REFERENCES

1. Archer, J. E. (2000). *Social Unrest and Popular Protest in England, 1780-1840, Volume*

   Cambridge University Press.

2. Bhorat, H., K. Naidoo, M. Oosthuizen, and K. Pillay (2016). Demographic, employment, and wage trends in South Africa.

3. Brandtzaeg, B. (1979). Women Food and Technology Case of India. *Economic and Political Weekly 14*(47), 1921–1924.

4. Brynjolfsson, E. and A. McAfee (2012). *Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*. Lexington Massachusetts: Digital Frontier Press.

5. Brynjolfsson, E. and A. McAfee (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies* (1st ed.). W. W. Norton & Company.

6. Central Intelligence Agency (2016). The World Factbook.

7. Cilliers, P. (2000). What Can We Learn From a Theory of Complexity? *Emergence* 2(1), 23–33.

8. Collins, R. (2010). Technological Displacement and Capitalist Crises: Escapes and Dead Ends. In *Review Literature And Arts Of The Americas,* pp. 23–34. University of Pennsylvania.

9. Cowen, T. (2011). *The great stagnation : how America ate all the low-hanging fruit of modern history, got sick, and will (eventually) feel better.* Dutton.

10. Cragg, J. (1963). Technological Progress, Investment and Full-Employment Growth.

11. *The Canadian Journal of Economics and Political Science 29*(3), 311–323.

12. Frey, C. and M. Osborne (2013). The future of employment: How susceptible are jobs to computerisation? Technical report, Oxford Martin School, University of Oxford, Oxford.

13. Friedman, T. L. (2007). *The world is flat : a brief history of the twenty-first century.*

   Douglas & McIntyre.

14. Haber, W. and M. L. Kahn (1957). Maintenance of Way Employment: I-Technological Displacement in Employment and Possible Moderating Measures. *Monthly Labour Review 80*(10), 1177–1182.

15. Harford, T. (2012). *The Undercover Economist.* Oxford University

   Press. Joubert, P. (2013). How many taxpayers are there really?

16. Le Roux, D. B. (2013). *Incongruence and enactment in information systems: a sense making analysis.* Phd, Stellenbosch University.

17. Lehman, T. (2015). Countering the modern luddite impulse. *Independent Review 20*(2), 265–283.

18. Levy, F. and R. Murnane (2005). *The new division of labor: How computers are creating the next job market. Princeton.* Princeton: Princeton University Press.

19. Marchant, G., Y. Stevens, J. Hennesy, and S. Day (2014). Technology, Unemployment & Policy Options:

20. Navigating the Transition to a Better World. *Journal of Evolution and Technology 24*(1), 26–44.

21. Mokyr, J., C. Vickers, and N. L. Ziebarth (2015, aug). The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? *Journal of Economic Perspectives 29*(3), 31–50.

22. Naude, W. and P. Nagler (2015). Industrialisation, Innovation, Inclusion.

23. Orlikowski, W. J. and D. C. Gash (1993). Technological frames: Making Sense of Information Technology in Organizations. *ACM Transactions on Information Systems 12*(2), 174–207.

24. O'Rourke, K. H., A. S. Rahman, and A. M. Taylor (2013). Luddites, the industrial revolution, and the demographic transition. *Journal of Economic Growth 18*(4), 373–409.

25. Rifkin, J. (1995). *The End of Work: The Decline of the Global Labor Force and the Dawn of the Post-market Era.* G.P. Putnam's Sons.

26. Rogers, E. M. (2003). *Diffusion of Innovations, 5th Edition*. (5 ed.). New York: Free Press.

27. Sabadash, A. (2013). ICT-induced Technological Progress and Employment: a Happy Marriage or a Dangerous Liaison ? A Literature Review. Technical report, European Commission Joint Research Centre Institute for Prospective Technological Studies, Luxembourg.

28. Sargent, T. (2000). Structural Unemployment Change in Canada. *Canadian Public Policy 26,* 1990–1999.

29. Strong, D. M. and O. Volkoff (2010). Understanding organization-enterprise system fit: a path to theorizing the information technology artifact. *MIS Quarterly 34*(4), 731–756.

30. The World Bank (2016). World Development Indicators.

31. Van der Berg, S. (2011). Current poverty and income distribution in the context of South African history.

32. *Economic History of Developing Regions 26*(1), 120–140.

33. Williams, R. and D. Edge (1996). The social shaping of technology. *ELSEVIER*

Research Policy 25, 865–899.

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