Information and Communications Technology and Employment in South Africa

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DECLARATION

I, Hlanganani Rabia Matjokana hereby, declares that the dissertation titled “Information and Communications Technology and employment in South Africa” submitted for the Master of Commerce at the North-West University is my own original work and has not previously been submitted to any other institution. I declare that no part of this work was submitted by other learners in the past. I further declare that all sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references.

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Hlanganani Rabia Matjokana

31 May 2022

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ABSTRACT

History has shown how industrial transformations in societies have been brought forward by technological advances as a result of advanced knowledge affecting the ways of work. With every industrial revolution, literature explains that it became evident that the introduction of innovative technologies impact the workforce in terms of employment levels and the requirement of new skills to complement the complexities that arise. The information and communication technology (ICT) sector has shown to be a critical factor in economic growth in numerous developed and developing countries and through this awareness, many institutions have over the past years invested in research and development (R&D) strategies that will allow for a smoother transition into and the adaptation of technological advancements brought about by the Fourth Industrial Revolution. However, many argue that the effects of ICT developments may have a negative impact on the labour market resulting in increased levels of technological unemployment as technology replaces human resources.

The decline in levels of employment in South Africa continues to raise concerns among organisations and policymakers. The study therefore investigates the impact of ICT on employment levels within the South African context. Many studies conducted on the relationship between ICT developments and employment are not unanimous in their conclusion regarding the existence of a causal relationship and a short-run or long-run relationship. This study employs an empirical approach in an attempt to investigate how ICT developments affect employment levels in South Africa. As a result, data on ICT components, economic growth, investments and income were collected from the World Development Indicator database while the labour statistics were gathered from Statistics South Africa for the period 1990 to 2020. The data were interrogated using econometric models to test for cointegration and causality. The Johansen cointegration test results indicated the existence of a long-run relationship among all variables and the vector autoregression (VAR) model determined that all the variables were significant determinants of employment in the long-run. Focussing specifically on ICT results, it was determined that ICT has a direct relationship with employment levels in the long-run, however, it was not a significant determinant of employment in the short-run as the results from the vector error correction model (VECM) showed. In addition, after conducting the Granger causality test to establish whether a bidirectional relationship exists between ICT developments and levels of employment, it was observed that these variables do not Granger cause each other. Finally, policy recommendations were proposed in accordance with the findings, which focussed on the major determinants, such as human capital development, which are more capable of impacting levels of employment.

Keywords: ICT, Fourth Industrial Revolution, Artificial intelligence, employment, labour force

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LIST OF ABBREVIATIONS

4IR:	**Fourth Industrial Revolution**
ADF:	**Augmented Dickey-Fuller**
AI:	**Artificial intelligence**
AIC:	**Akaike Information Criterion**
BIC:	**Bayesian Information Criterion**
DTI:	**Department of Trade and Industry**
ECM:	**Error Correction Model**
FPE:	**Final Prediction Error**
GDP:	**Gross Domestic Product**
H_0:	**Null hypothesis**
H_1:	**Alternative hypothesis**
HQC:	**Hannan-Quinn Criterion**
ICT:	**Information and communications technology**
IoT:	**Internet of Things**
KPSS:	**Kwiatkowski, Phillips, Schmidt and Shin**
LM:	**Lagrange Multiplier**
NDP:	**National Development Plan**
NPC:	**National Planning Commission**
NQF:	**National Qualifications Framework**

NREDS:	**National Research and Experimental Development Survey**
OLS:	**Ordinary least square**
PAC:	**Principal component analysis**
PP:	**Phillips-Perron**
R&D:	**Research and development**
SARB:	**South African Reserve Bank**
SIC:	**Schwarz Information Criterion**
STATS SA:	**Statistics South Africa**
STEM:	**Science, Technology, Engineering, and Mathematics**
VAR:	**Vector Autoregression**
VECM:	**Vector Error Correction Model**
WDI:	**World Development Indicator**
WEF:	**World Economic Forum**

CHAPTER 1

INTRODUCTION AND BACKGROUND

1.1 Introduction and background to the study

Advancements in Information, Communication and Technology (ICT) and the merger of fields that are exploring artificial intelligence (AI), cutting-edge robotics, the Internet of Things (IoT), cloud computing, cyber security and big data analytics have pushed the world to exploit what is now called the Fourth Industrial Revolution (4IR) – a term coined by Klaus Schwab in 2016. This idea of the 4IR has created much division among academics from all spheres of research in terms of the opportunities and challenges brought forth by this era. Some see the potential of exponential growth in economies, while others view the transformation as having a lagging effect, especially on developing countries that fail to exploit this industrial's potential (Asghar et al, 2020).

History has shown how industrial transformations in societies have been brought forward by technological advances as a result of advanced knowledge affecting the ways of work (Wessels, 2020:1). The First Industrial Revolution was characterised by mechanised manufacturing and coal powered energy turning water into steam powered engines in the 1760s and this required a new breed of skills in the mechanisation of production (Cunningham, 2018). This was subsequently followed by the Second Industrial Revolution in the 19th century, which saw the invention of more improved sources of energy such as electrical and oil power, enabling the mass production of goods through assembly lines, synthetic processes and mechanical sectors, which saw the design of aeroplanes (Kazancoglu & Ozkan-Ozen, 2017). The third era saw a digital move towards technologies that enabled energy intensive industrial sectors adopting advanced ways of processing raw materials using electronics and precision mechanics to bring forth the computerisation of industries and smart factories (Postelnicu & Calea, 2019). Building on the Third Industrial Revolution is the 4IR, which is said to be one that describes a world where human beings "move between digital domains with the use of connected technology to enable and manage their lives" (Xu et al, 2014:90; Corfe, 2018). This fourth wave builds on the third industrial revolution and is characterised by a fusion of technology that is blending the lines between the biological, digital and physical spheres (Manda &

Dhaou, 2019:245). The 4IR has therefore brought a shift in the way that technology, communication, data and analytics affect the way people live, interact with each other, and work (Manda & Dhaou, 2019:245).

Controversial conversations have since been the main topics of critique among the interested and affected parties regarding this complex era that is combining humans and machine (Wessels, 2020:1). Martin (2018) argues that this complex and blurred picture is bound to remain puzzling as developments in ICT continue to be the driving force behind the 4IR and that the only clear current viewpoint is the importance around the need for skills in the digital realm for future world of work. It has become clear that with the introduction of every industrial revolution, new skills are needed to complement the complexities that arise as explained by McGowan (2017) in Figure 1.1.

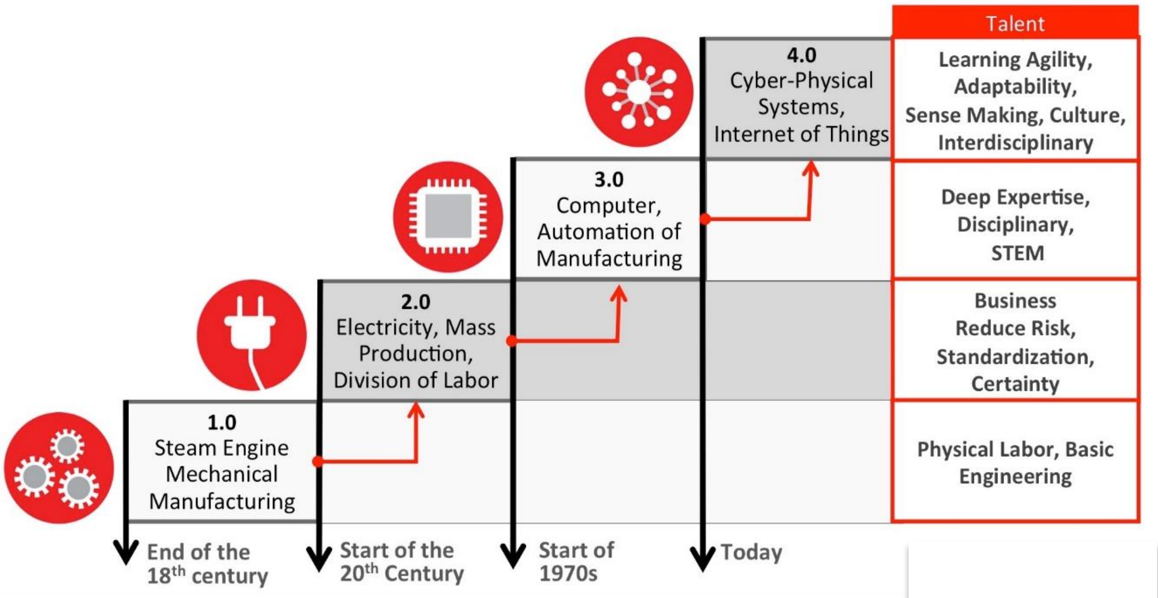


Figure 1.1: Stages of industrial revolutionary skills development (McGowan, 2017:2).

Looking at McGowan's (2017) explanation of the 4IR in light of the South African context, it may seem as though this new transformative era of ICT may be bringing more complex challenges than opportunities, and therefore the reason for this study.

South Africa has been struggling with the major issue of unemployment, mainly as a result of low economic growth. According to the narrow definition of unemployment, Statistic South Africa (Stats SA) reported an unemployment rate of 32.5% in the fourth quarter of

2020 (the highest since the quarterly survey data became available in 2008), which meant that 7.2 million people were unemployed during that period – a 2.5% increase from the previous quarter, while the expanded definition (which includes those who are discouraged from seeking work) puts unemployment levels at 42.6% (Stats SA, 2020). About 52.3% of those who are unemployed have been found to have education levels below Grade 12 (National Qualifications Framework (NQF) Level 4) in comparison to a mere 1.8% of the unemployed being graduates and 7.5% having other tertiary qualification (Stats SA, 2020). It was also noted that unemployment was mainly prevalent among youth – with those between the ages of 15 and 24 accounting for 63.2%, and those aged between 25 and 34 accounting for 41.2% (Stats SA, 2020). Maluleke (2020), cited that "the proportion of people of working age, versus the proportion of those that are employed, is widening, meaning the market is not creating sufficient jobs to absorb enough people".

On a technological front, ICT's contribution to the country's GDP was slightly higher than 2.7% in 2020 – in other words, for every R100.00 that the economy produced that year, R2.70 was as a result of activities related to ICT (Stats SA, 2020). These activities were related to telecommunication services that include, among other things, private broadcasting and cell phone services, computer services (data processing and software development), manufacturing of ICT equipment (electronic components and devices) and the development of content and media (Stats SA, 2020). South Africa has been experiencing a trade deficit as it consistently imported more ICT products than it has exported and this deficit has grown since 2011, from R42 billion to R97 billion in 2020 (Stats SA, 2020). Almost half of ICT imports consisted of communication equipment and information supply services, and about 30% consisted of office and computing machinery. This is evidence that innovation and technological changes continue to play an important role in South Africa's economic growth. ICT plays a vital role in modern society as it has become instrumental in contributing to economic growth where new enabling technologies are underpinning innovation and creativity in every sector and have now been reported to be responsible for close to half of the productivity growth in the country (DST, 2019).

Therefore, for the country to mitigate against a potential disruption brought about by digital technology, it needs to embrace and include innovative practices that would align the workforce into a competitive and sustainable productive entity. The effective uptake and utilisation of ICT requires large investments in innovation, research and development (R&D), and human capital development, both mid-level and high-level skills, to create the requisite absorptive capacity in the economy. This is because the transformation brought about by this digital age is unavoidable and all institutions are currently and will be affected by it (Wessels, 2020:3). The country should expect that as much as the previous industrial revolutions have had an impact on socio-economic conditions, so will the functioning and operations of the world of employment be (Xing & Marwala, 2017). Brynjolfsson and McAfee (2014) point out that advancements in digital technologies have the potential to disrupt labour markets, which could result in greater inequality through the reallocation of income and wealth. The authors are of the opinion that as automation substitutes labour in all economies, the overall displacements of labour may intensify the gap between returns to labour and returns to capital. These digital technologies have the ability to reproduce innovations, insights and valuable ideas at marginal costs therefore generating wealth for the innovators and diminishing labour demand for lower skilled workers (Brynjolfsson & McAfee, 2014). However, there also exist a possibility that technological displacement of labour may cumulatively lead to a net rise in more rewarding and safer jobs (Schwab, 2016:3).

The motivation behind this study was to examine the existence of a relationship between ICT developments and levels of employment.

1.2 Problem statement

The accelerated and complex revolutionary power of the current ICT-driven industrial era, fuelled by globalisation, is rapidly leading to more careers becoming obsolete with robotics and AI replacing most jobs and threatening an increase in one of the main challenges faced by South Africa, namely unemployment (Preble, 2017). According to Stats SA (2020), unemployment rose to a level of 32.50% in the fourth quarter of 2020 from an average of 25.99% between 2000 and 2009 (Tradingeconomics.com, 2021).

In this current 4IR era, R&D is geared towards ICT developments that are shaping the world of work across all sectors and South Africa's spending on R&D has continued to increase with the National Research and Experimental Development Survey (NREDS) recording the country's gross expenditure on R&D at a growth rate of 3.1% year-on-year. Gross expenditure on R&D as a percentage of the country's GDP moved from 0.53% to 0.83% between 2008 and 2018 (DST, 2019).

An observation of these statistics and the relationship between rising unemployment and an increase in R&D and ICT developments reveals what may be of concern to the policymakers. The relatively high levels of unemployment experienced in the past ten years followed by a huge spike in 2020 indicate that South Africa needs to take serious note of the implications of the current transformations in light of preparing the workforce for opportunities brought about by the ICT developments and the future of jobs.

This problem statement was derived from taking into consideration the need to better understand developments in ICT and their influence on employment levels in South Africa and it is guided by how key functions in South African institutions should be transformed in order to better prepare the workforce for the current 4IR. The major concern with regard to the rapid transformations brought about by the ICT developments is the potential loss of employment brought about by the automation of numerous jobs, rendering human capital obsolete and therefore further contributing to the scourge of unemployment. According to a World Economic Forum report published in 2016, in Africa alone, about 230 million jobs will require digital skills by 2030 and this has put a need for higher education institutions to respond to these demands. The quality of the education system in South Africa and the basic accessibility issues have prompted organisations to take it upon themselves to prepare their own labour force for the inevitable transformations by encouraging a learning culture (Getsmarter, 2021). Alongside these developments, the country's government has also committed to catapulting the country into the 4IR in their presidential commission's recommendations by investing in human capital development, creating an AI institute, securing and availing data to enable innovation and building 4IR infrastructures (Getsmarter, 2021).

Furthermore, the study looks at measures that are being implemented by the government and corporate institutions to ensure that this transformation is managed wisely with minimum negative effects on the country's labour force and better socio-economic yields in terms of eradicating poverty and reducing inequality and unemployment.

1.3 Research questions

In order to derive the research question, certain considerations needed to be taken in order to accurately understand ICT and employment in South Africa. The main research question guiding this study is:

- What are the directions of causality between ICT and employment in South Africa?
- How has ICT developments impact employment in South Africa and how should the key functions of South African institutions be adapted in preparation for the future workforce?
- What is the spill-over influence of ICT development and employment in South Africa?

1.4 Objectives of the study

1.4.1 Primary objective

The primary objective guiding the study is to investigate the relationship between ICT and employment in South Africa.

1.4.2 Theoretical objectives

The theoretical objectives of this study are to:

- Explore the various stages of industrial revolutions with a focus on ICT development as the key driver of the 4IR.
- Identify the labour force population segment that could potentially be affect by ICT developments.
- Identify the labour force population segment that stands to benefit from ICT development.
- Recommend mitigating strategies for the risks of this phenomenon and strategic plans for leveraging on opportunities.

1.4.3 Empirical objectives

The empirical objectives of this study are to:

- Detect the direction of causality between ICT and employment in South Africa.
- Investigate the impact of ICT on employment in South Africa and analyse the extent to which these ICT developments have had an effect (whether positive or negative) on the labour force.
- Determine the spillover influences of ICT development and employment in South Africa.

1.5 Contribution of the study

With these new developments in ICT posing both opportunities and challenges, studies in all affected sectors of society have rapidly increased over the past years. South Africa has had a highly unequal and poverty-stricken society mainly due to high levels of unemployment and the need for the country to reduce these levels may be met with resistance from the developments brought about by ICT transformations. The impact of ICT developments on employment levels have been debated by both optimists (technophiles) and pessimists (technophobes) with the former advocating for the advancement of these developments while the latter views the changes from a destructive point of view. Literature substantiates that there exists a relationship between ICT developments and employment. However, in the context of the South African economy, the empirical literature reveals a gap in the studies that have been conducted and that there are not enough empirical studies that examines the impact of ICT on employment, while very little is known about the causal relationship between the two variables. A focus will therefore be put on examining the correlation between these variables by interrogating multiple data sets from all drivers of these ICT developments. The findings in this study are intended to contribute knowledge to the wider research community looking at institutional practices, policy and academic theory with the aim of highlighting the approaches that could be implemented in South Africa to better align and prepare the society – more especially the labour force – for the future skills required to curb the potential unemployment challenge that leads to poverty and inequality.

1.6 Chapter classification

This section provides guidance to the content of the various chapters in the study.

Chapter 1 focusses on the introduction and background information of the study while outlining the various aspects relating to ICT and employment. Clarification is further given on the rationale of undertaking this study by specifying the problem statement and objectives. Chapter 2 gives an in-depth analysis on the labour market outcomes and ICT developments in South Africa by focussing on concepts, definitions and trends. Chapter 3 explores literature in terms of concepts on ICT and employment and the relationship between the variables. Chapter 4 focusses on the research methodology employed in the study by outlining the research design and the processes used to collect the research data including the analytical techniques. Chapter 5 presents the results obtained from the study and provide a discussion on their interpretation. The final chapter concludes the findings of the empirical study and provides recommendations in accordance to the findings.

CHAPTER 2

OVERVIEW OF LABOUR MARKET OUTCOME AND ICT DEVELOPMENTS

2.1 Introduction

South Africa is faced with the three main challenges of unemployment, poverty and inequality. Policymakers have adopted the National Development Plan (NDP) as a framework towards creating inclusive economic growth forecasted at mitigating those challenges. The country has seen annual increases in unemployment in line with the stagnant economic growth that has led to minimum growth opportunities. However, the government has been putting measures in place to stimulate growth capable of absorbing the large pool of unemployed labour.

The ICT sector has shown to be a critical factor in economic growth in numerous developed and developing countries and through this awareness, many institutions have over the past years invested in R&D strategies that will allow for a smoother transition into and the adaptation of technological advancements brought about by the 4IR. This chapter provides an overview of the state and performance of the labour market and ICT in South Africa. The data utilised in this section reveal the trends in both employment and ICT activities in order to set a foundation for the analysis in chapters to follow.

2.2 Overview of labour market outcome

2.2.1 Concepts, definitions and labour market dynamics

Labour market dynamics are a result of complex interaction happening within and between economic institutions where human resources are endlessly reallocated across organisations, industries and geographic locations (Guerrero & Axtell, 2013). It is essential to begin by asking who the labour market is and how it works. Kaufman and Hotchkiss (2003) explain it as a place where buyers and sellers of labour interact. A market place exists whenever there is a demand (from the buyers) and supply (from the seller) of good and services, and in the labour market, labour services are negotiated between buyer and seller (Didier, 1997). It is those negotiations that influence the placement of labourers in jobs with specific employment conditions, benefits and wages (Kaufman & Hotchkiss, 2003). In the labour market, organisations take up the role of buyers, also as bidders in terms of working conditions and remuneration, while individuals perform the role of sellers, offering their skills, knowledge and experience to employers (Serena, 2016). The labour market functions on the principle of competition where the individuals compete against one another in an attempt to secure a contract. Similarly, organisations compete to attract and retain the most effective and efficient employees with the aim of making profits. According to Serena (2016), "the labour market is the market in which the amount of services that correspond to tasks well established in the job description, are offered for a price or remuneration". Labour demand is derived from an employer's need for labourers to produce goods and services and organisations select their employment levels based on factors such as the costs associated with labour, workforce productivity, current and forecasted production levels and prices that the organisation can request for its products (LMIRU, 2005:3). Therefore, when organisations expand their operations or replace workers who are departing from their employment, job opportunities are created. Labour supply, on the other hand, alludes to the population within the labour force currently employed or actively searching for jobs. The extent to which the labour supply fluctuates is governed by factors such as the proportion and age distribution of the population who are of working age, education and training levels, retirement patterns, economic conditions, migration trends and different choices regarding the time allocation between leisure and work (LMIRU, 2005:3). Inasmuch as the labour market can be defined in terms of supply and demand, there exist some unique elements that restricts this theoretical framework's applicability (Kaufman & Hotchkiss, 2003). When looking at the basic theory of supply and demand, it can be predicted that when supply exceeds demand, prices are expected to drop to a point where the surplus is removed. However, in the labour market, excess supply rarely translates into reduced prices/wage rates, and likewise, excess demand does not normally lead to an increase in the price/wage rate, therefore deviating from the supply and demand theoretical framework (Kaufman & Hotchkiss, 2003). A major contributing factor to this deviation on labour market outcomes include institutional forces – the impact that institutions such as unions, government and companies have on the labour market. These forces come as a result of institutions developing and implementing policies and regulations that govern the functioning of the labour market (Benjamin, Gunderson, & Riddell, 2003).

The labour market constitutes people who are employed, unemployed and those who are not economically active within the working-age population. When defining the working-age population, the minimum age limit tends to be country specific and dependant on systems of the state such as the mandatory schooling age and the minimum age for admission to employment (Pietschmann et al, 2016). In most countries, the working-age population is defined as the proportion of the population aged 15 years and older, while in South Africa it only refers to those aged between 15 and 64 years (Stats SA, 2019). Table 2.1 highlights terms and concepts related to the labour market as explored in this section.

Typology	Main Characteristics
Employed	These are people who are working, or who are absent from work but say that they have a job that they will return to.
Furloughed workers	This group includes temporarily absent workers as well as workers who report working for zero hours and having zero earnings
Not economically active	This group of people are not working and not looking for work. It typically contains retirees, students, and full-time caregivers
Discouraged unemployed	These are people who are not employed, and are available and willing to take up work within the next week, but are not actively searching for employment
Searching unemployed	These are people who are not employed, and are available and willing to take up work within the next week, and have been actively searching for employment in the recent past.
Unemployment rate (narrow)	Is obtained by taking the ratio of the number of people who are actively searching for work, divided by the number of people who are either employed or actively searching for work.
Unemployment rate (broad)	Is obtained by taking the ratio of the number of people who are in either of the unemployed groups, divided by the number of people who are in either of the unemployed groups or are employed.
Employment rate (narrow)	Is the ratio of the number of people in employment, divided by the number of people who are either employed or searching unemployed
Employment rate (broad)	Is the ratio of the number of people in employment, divided the number of people who are either employed or searching unemployed or discouraged unemployed
Employment-to-population ratio	Provides a measure of the fraction of people in a population that are employed. It differs from the employment rate because it does not differentiate between people who are not economically active and people who are unemployed.
Labour force	The number of people that are employed plus those who are unemployed constitute the labour force or economically active population.

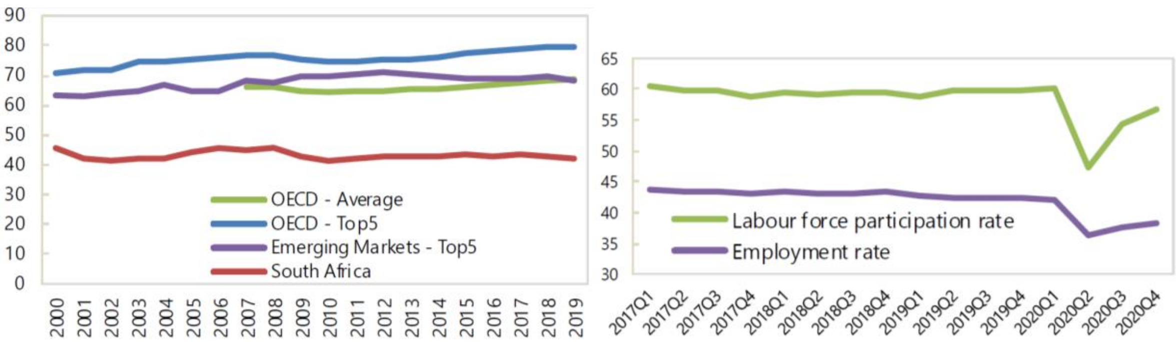
Table 2.1: Typology of labour. Source: Rachhod & Daniels, 2020.

South Africa has come a long way in social and economic development after the 1994 democratic election, yet the economy still experiences structural challenges of unemployment, poverty and inequality (Anand, Kothari, & Kumar, 2016). After rejoining the international trading community and the country's integration into the product markets and global capital, South Africa depended on the idea of export-led growth in order to escape the stagnant economic environment (Burger & Woolard, 2005). The country had a huge supply of unskilled and low-skilled labour of which according to trade theory should lead to specialisation of goods that depend on this kind of labour. But due to institutional factors, the level of wages for some labourers were higher than natural market-clearing levels resulting in employers finding the unskilled and low-skilled labour less attractive than the better skilled labour (Burger & Woolard, 2005). One of the driving forces of unemployment has been argued to be a mismatch between the supply of skills and demand and a shortage in quality education. Anand, Kothari and Kumar (2018) posit that "skill biased technical change and decline in mining and agriculture has held back demand for low skilled workers", and the influx into the labour market by black Africans after the abolishment of apartheid further increased low-skilled labour into the labour supply, therefore accounting for a rise in unemployment (Banerjee *et al.* 2008).

2.2.2 Labour market trends

The impact of technology on the labour market has been deemed complicated and unpredictable. However, Balalle and Balalle (2016:151) point out an inevitable situation of which the demand for technological and soft skills will be very high, replacing the demand for manual and physical skills in the future workplace. As sophisticated algorithms and AI automate individual tasks, a lot of function become redefined as other jobs are created while some disappear (WEF, 2016). A large proportion of the global labour force consists of lower skilled employees performing mostly manual tasks that are easily automatable by technology and the demand for these skills will continue to decline across most industries (Balalle & Balalle, 2016:152). Advanced technologies require workers with basic and advanced technological skills who are able to comprehend how they function, are innovative, possess cognitive skills such as complex information processing, critical thinking and creativity, and can easily adapt to changing working environments (Bordoloi & Matsuo, 2001). The WEF (2016) estimates that over 50% of all occupations that will be required to include these core skills currently do not. This is a result of jobs being lost through the introduction of computerised routine jobs and robotics on assembly lines. South Africa faces a more pressing challenge with a shortage of high skilled employees, especially those possessing digital skills and an abundance of low to middle-skilled workers, therefore posing a threat of higher unemployment.

In quarter one of 2021, South Africa had a population of just over 60 million and a total labour force of 22.24 million (with employed people accounting for 14.99 million and unemployed people at 7.24 million). Discouraged work-seekers and those who were not economically active accounted for 3.13 million and 14.09 million in the working-age population, respectively (Stats SA, 2021). The unemployment rate reached its highest ever recorded figure of 32.6% and an absorption rate of 38.0%, while the labour force participation stood at 56.4%. This aggregate employment rate is considered too low when comparing these statistics to international standards as observed in Figure 2.1, and the country's low employment rate mirrors both extremely high structural unemployment and low labour force participation.



Key labour market indicators	Jan-Mar 2020	Jan-Mar 2021	Year-on-year change
	Million		
Population 15-64 yrs	38,87	39,46	1,5
Labour force	23,45	22,24	-5,2
Employed	16,38	14,99	-8,5
Unemployed	7,07	7,24	2,4
Not economically active	15,42	17,22	11,6
Unemployment rate (%)	30,1	32,6	2,5
Employment/population ratio (Absorption) (%)	42,1	38	-4,1
Labour force participation rate (%)	60,3	56,4	-3,9

Figure 2.1: Key labour market indicators — labour market participation. Source: Stats SA (2021) and Duval and Shibata (2021)

Over a one-year period (2020–2021), the working-age population increased by 1.5%. The labour force decreasing by 5.2% as a result of employment levels decreasing by 8.5% to almost 15 million people employed, while unemployment increased to 7.2 million (32.6%) (Stats SA, 2021). This very high level of unemployment, which was already increasing before the Covid-19 pandemic, has been cited to contribute to the low labour participation rate by discouraging the search for employment (Duval & Shibata, 2021). It was observed that high unemployment is concentrated among the low to middle-skilled and the youth (fig. 2.2). In the first quarter of 2021, the unemployment rate of individuals aged 15–24 stood at 63.6% relative to 59% the previous year, versus only 13.1% for the group aged 55–64 (Stats SA, 2021). It was also evident that the lower- to middle-skilled group (those without matric) suffered high unemployment at about 38.3% in comparison to 7.5% among graduates with a tertiary degree.

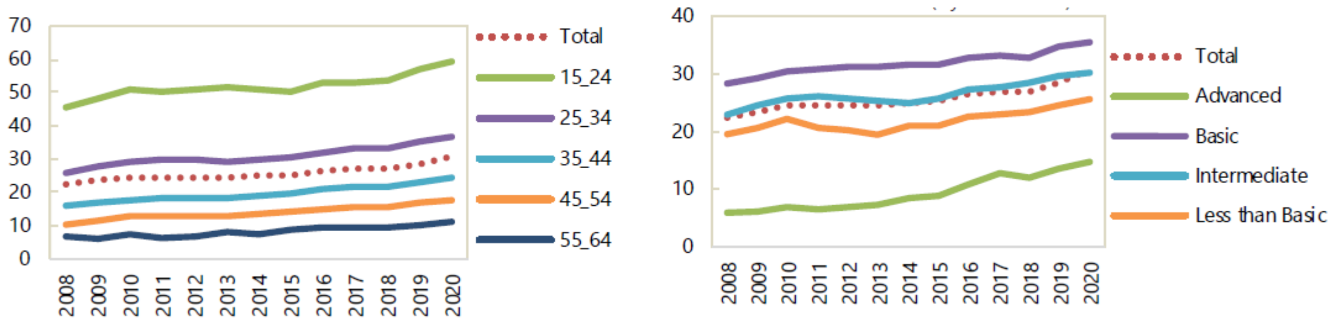


Figure 2.2: Unemployment rate by age and by level of education. Source: Duval and Shibata, 2021

South Africa has shown a high level of long-term unemployment (defined as unemployment lasting more than a year) and these high levels normally signify the economy's incapability of creating sufficient employment to sustain the working-age population. This according to South Africa's Department of Trade and Industry (DTI) is a result of the structural nature of unemployment in the country and the inability of many skilled sectors to fill certain positions due to a shortage of higher skilled labour (DTI, 2004). Therefore, if the country continues to fail addressing the skills shortage, high levels of unemployment will dominate the labour market.

2.3 Overview of ICT developments

Global digitisation has become a driving force in socio-economic change in the current era, where innovations in technology and economic easing have resulted in transformations in the global economy over the past few decades, drastically impacting production forces and power relations at local, national and international levels (Sen, 1999). In the 21st century, the generation of information, its processing and transmission significantly determine the beneficiaries of the transformative potential of this information economy (Castells & Himanen, 2013). Mobile voice and internet services have brought this potential to developing countries throughout the world and effectively connecting countless inhabitants on the African continent and it is for such reasons that ICTs are viewed as important driving forces for developing countries to move towards the United Nation's 2030 Agenda for Sustainable Development (NPC, 2020). ICT developments have proven to not only improve outputs through simplified information flow and minimal transaction costs, but also boost the welfare of societies with easy access to internet connection (Grunder, Hatonen, & Koutroumpis, 2014). The dissemination of ICT and interconnectedness across the globe provides huge potential to quicken progress and create knowledge and inclusive societies by eradicating poverty and inequality.

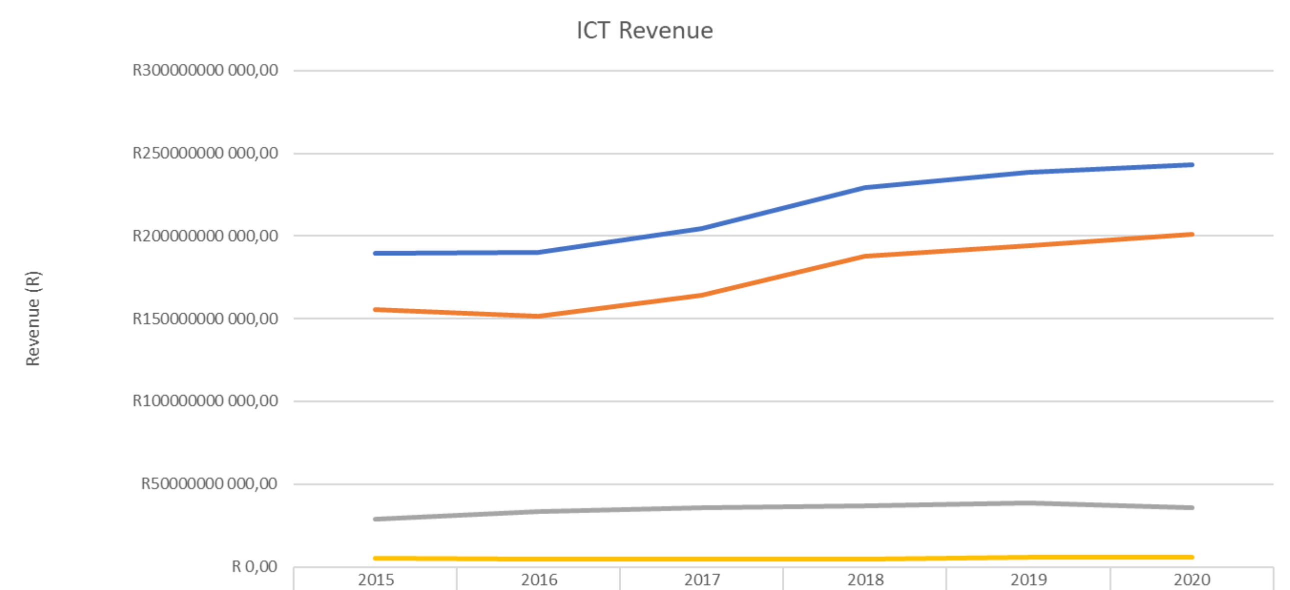
According to a paper by the National Planning Commission (2020), secondary improvements in the economy have been strongly linked to investments in telecommunication infrastructure, which bring about efficiencies in transactions and information flows. Although South Africa has shown a 51% internet penetration rate, there has not been much positive network effects experienced in comparison to other economies with comparable internet penetration rates and economic status (Gillwald & Mothobi, 2019). The country's policymakers have, however, suggested that it may not necessarily be the supply-side barriers of quality, price and availability of communication that affect internet use and access, but the demand-side constraints also contribute significantly. These include the affordability of services and technological devices, the availability of appropriate local content in the languages understood by the user and the knowledge capability to use digital services (NPC, 2020).

The 2019 global Covid-19 pandemic saw digital technologies becoming a very crucial connectivity enabler facilitating continuous living and connecting societies in an unprecedented manner. The lockdown restrictions forced people to turn to technological devices and internet connectivity as substitute tools for contact activities and most of these habits are likely to continue until a possible long-run solution is available (ICASA, 2021). This has placed great importance on the need for a reliable digital infrastructure in order to facilitate critical activities such as working and learning remotely, online banking services, logistics and food delivery, telemedicine and remote entertainment (ICASA, 2021).

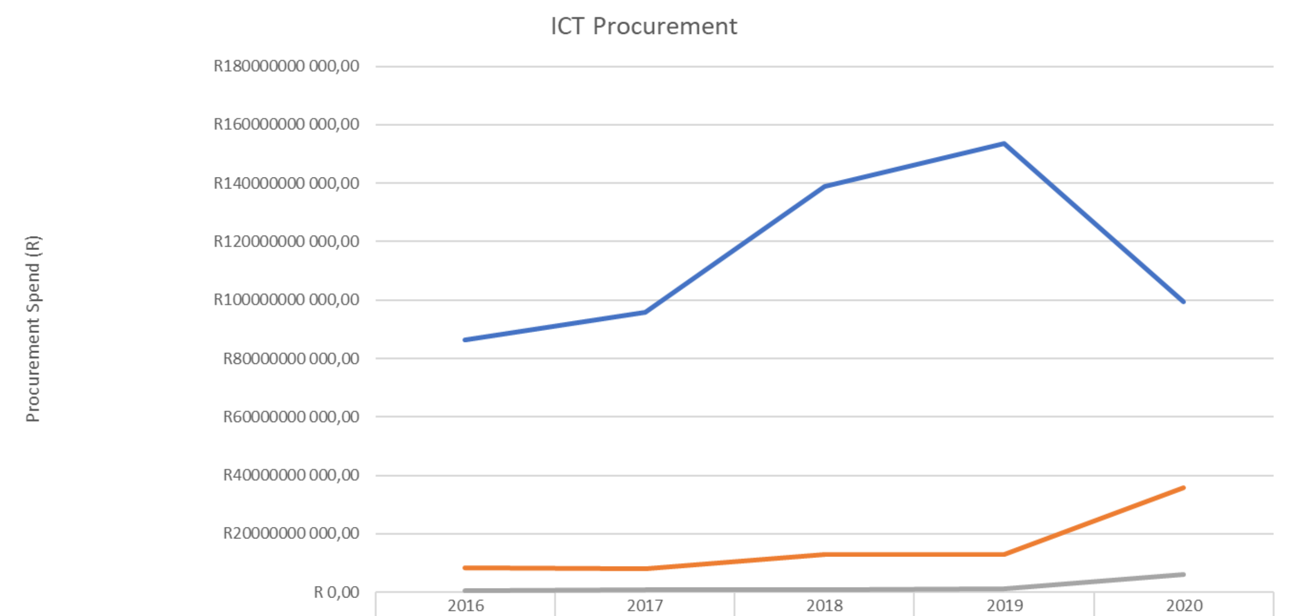
2.3.1 State of ICT in South Africa

In comparison to other African countries, South Africa's ICT market is one of the most advanced and developed regardless of constant implementation delays in regulations and policies intended at enabling the roll-out of the integrated infrastructure plan for digital development (NPC, 2020).

The total ICT market in South Africa (which comprises telecommunication, broadcasting, and postal) reported total revenue of R243 billion in 2020 – a 2% increase from 2019 and an average of 5.1% annual increase for a period of six years (fig 2.3) — contributing 3.1% to the country's GDP in 2020 (ICASA, 2021). The telecommunication services contributed the largest share of R201 billion (about 83% of the ICT market) and will therefore be the focus in this section. In terms of procurement, the total telecommunication service expenditures were at R99 billion in 2020, a 35.3% decrease from the previous year (ICASA, 2021)



	2015	2016	2017	2018	2019	2020
Total Sector Revenue	R189727239 150,00	R190044525 308,00	R204386608 276,00	R229296293 291,00	R238351239 862,00	R243019264 975,00
Telecommunication Revenue	R155731039 861,00	R151569024 076,00	R163987306 320,00	R187587374 843,00	R194284132 172,00	R201254592 538,00
Broadcasting Revenue	R28688718 290,00	R33655415 072,00	R35606415 286,00	R36921489 746,00	R38325761 969,00	R35814897 915,00
Postal Revenue	R5307481 000,00	R4820086 160,00	R4792886 670,00	R4787428 702,00	R5741345 721,00	R5949774 522,00

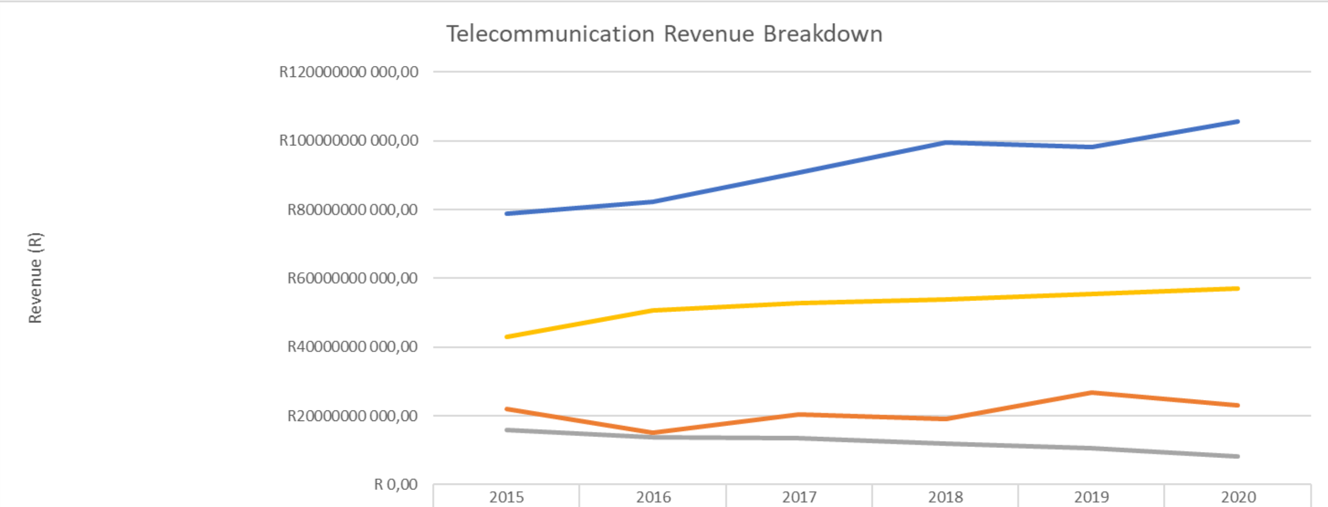


	2016	2017	2018	2019	2020
Telecommunication Procurement Spend	R86448461 080,00	R95898396 437,00	R138796397 264,00	R153709327 406,00	R99474448 024,00
Broadcasting Procurement Spend	R8267951 961,00	R8133329 927,00	R12916707 224,00	R12966834 308,00	R35814897 915,00
Postal Procurement Spend	R555395 857,00	R817935 346,00	R747631 839,00	R1212745 251,00	R5949774 522,00

Figure 2.3: ICT revenue and procurement trends. Data source: ICASA, 2021.

When breaking down the telecommunication sector activities, the total mobile services revenue (which includes mobile data services, voice services, text and multimedia services, outbound roaming and other mobile services) was reported at R105 billion in

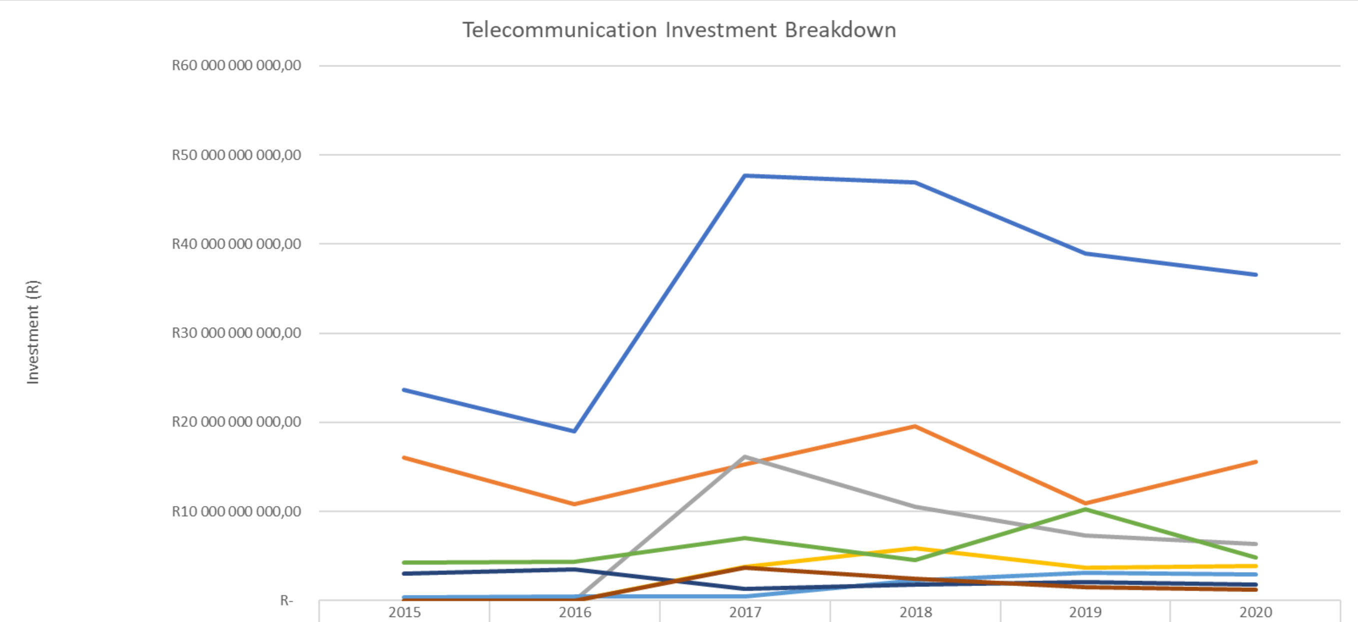
2020, with mobile data and voice services accounting for 80% of the revenue. The total mobile services revenue showed an average annual increase of 6% for a period of six years. The total fixed internet and data, (which includes fixed wired-broadband services, fixed internet, and other telecommunication services such as leased lines and fixed value-added services), reported a revenue of R23 billion in 2020. Total fixed line (consisting of fixed-telephone subscription charges, fixed-telephone calls, and retail fixed-telephone services) had a revenue of R8 billion, decreasing by 12.6% for a period of six years (Figure 2.4). Prepaid mobile voice, data and messaging revenue were reported at R57 billion in 2020 (ICASA, 2021).



	2015	2016	2017	2018	2019	2020
Total Mobile Service Revenue	R78838681 356,00	R82209711 759,00	R90737963 135,00	R99569265 222,00	R98071800 081,00	R105670253 917,00
Total Fixed Internet and Data Revenue	R22023113 787,00	R15227779 522,00	R20432607 468,00	R19078304 740,00	R26790096 707,00	R23061826 922,00
Total Fixed Line Revenue	R15809963 943,00	R13736287 016,00	R13416021 437,00	R11928767 258,00	R10653960 614,00	R8083204 765,00
Prepaid Mobile Voice, Data, & Messaging Revenue	R42967191 708,00	R50583604 396,00	R52889153 267,00	R53802738 901,00	R55568606 438,00	R57144609 209,00

Figure 2.4: Telecommunication revenue breakdown. Data source: ICASA, 2021

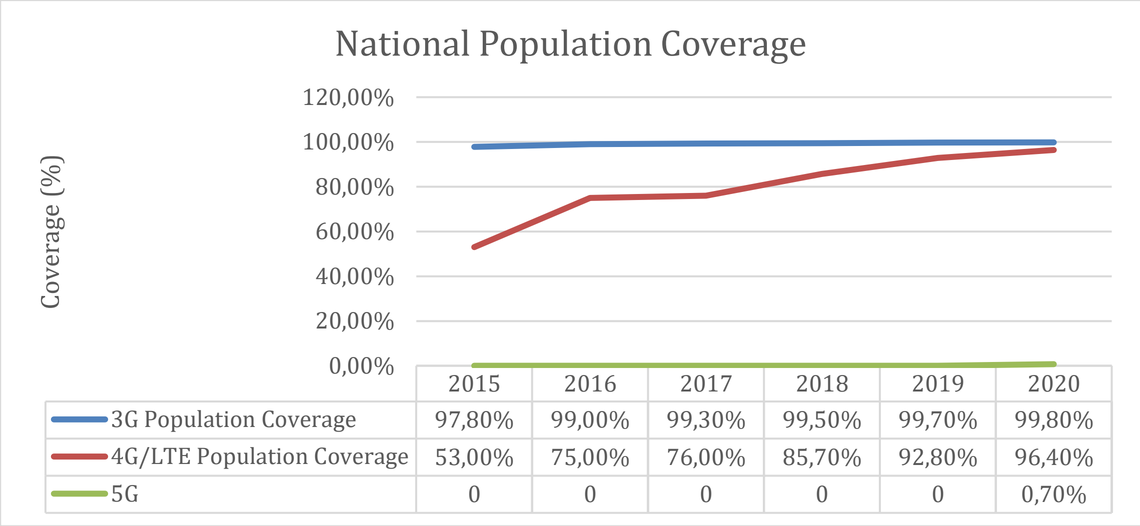
The total telecommunication investment has continued to decrease from over R14 billion in 2017 to about R36 billion in 2020 as seen in Figure 2.5.



	2015	2016	2017	2018	2019	2020
Total Telecommunication Investment	R23 639 670 771,00	R19 031 129 037,00	R47 628 221 569,00	R46 933 416 166,00	R38 902 355 901,00	R36 555 514 067,00
Mobile Communication Services	R16 023 808 303,00	R10 773 379 404,00	R15 237 727 593,00	R19 584 646 672,00	R10 922 347 986,00	R15 609 753 461,00
Expansion	R-	R-	R16 176 231 342,00	R10 482 529 163,00	R7 265 057 850,00	R6 380 976 746,00
Infrastructure	R-	R-	R3 770 800 407,00	R5 916 132 762,00	R3 729 768 720,00	R3 894 797 426,00
Fixed-telephone Services	R362 678 821,00	R430 713 855,00	R480 671 041,00	R2 226 456 703,00	R3 110 456 703,00	R2 912 024 038,00
Fixed (Wired)-Broadband Services	R4 271 046 025,00	R4 348 617 012,00	R7 002 587 357,00	R4 559 607 770,00	R10 221 560 045,00	R4 830 520 473,00
Other Telecommuncation Services	R2 982 137 563,00	R3 478 418 766,00	R1 285 335 724,00	R1 812 969 770,00	R2 113 372 650,00	R1 747 952 845,00
Maintenance	R-	R-	R3 674 868 105,00	R2 431 073 325,00	R1 539 791 654,00	R1 179 115 659,00

Figure 2.5: Telecommunication investment breakdown. Data source: ICASA, 2021

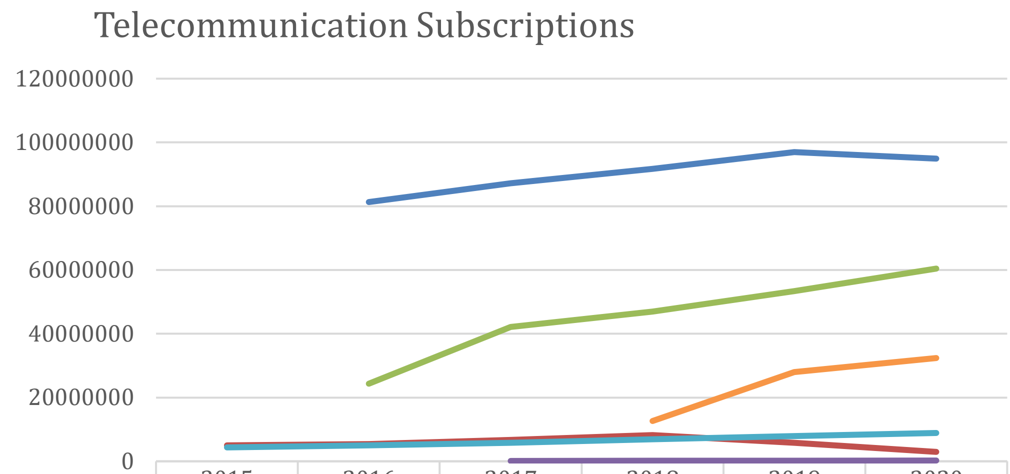
In terms of national population coverage, 3G was at 99.8%, 4G/LTE at 93.4%, and 5G at only 0.7% in 2020 (Figure 2.6).



	2015	2016	2017	2018	2019	2020
3G Population Coverage	97,80%	99,00%	99,30%	99,50%	99,70%	99,80%
4G/LTE Population Coverage	53,00%	75,00%	76,00%	85,70%	92,80%	96,40%
5G	0	0	0	0	0	0,70%

Figure 2.6: National population coverage. Data source: ICASA, 2021

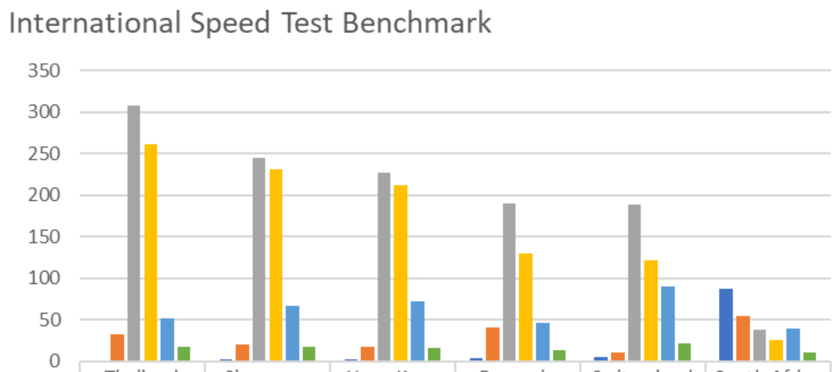
In 2020, mobile cellular subscriptions (which includes data, prepaid and post-paid voice) were recorded at 94 million, fixed line (voice and broadband) standing at 2 million, smartphone subscriptions were recorded at 60 million, wireless-broadband was only at 244 879, while the total number of LTE devices stood at 32 million. It was also reported that machine-to-machine subscriptions – “an industrial mobile data subscription directed at communication between machines” – stood at almost 90 million (ICASA, 2021; Telenor, 2021).



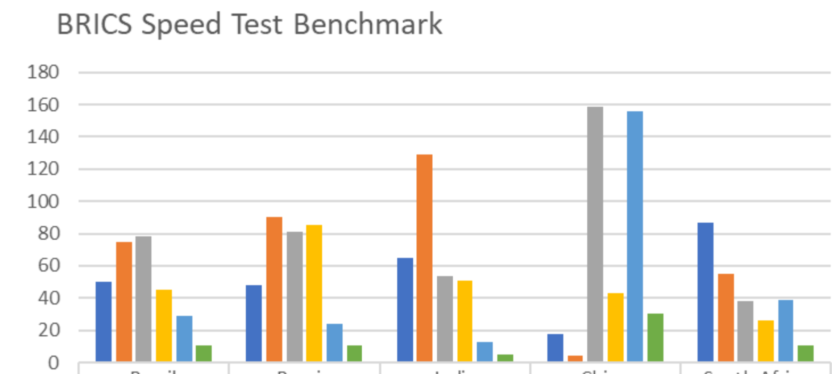
	2015	2016	2017	2018	2019	2020
Mobile Cellular Subscription		81314463	87153108	91707731	96972459	94952509
Fixed Line Subscription	4955387	5406439	6669177	8225243	5811706	2955633
Smartphone Subscription		24340341	42094018	46904835	53380748	60438901
Wireless-Broadband Subscription			115951	185327	231687	244879
Machine-to-Machine Mobile Subscriptions	4357508	4971928	5806477	6890330	7893326	8885075
Total Number of LTE Devices				12644364	27999204	32387272

Figure 2.7: Telecommunication subscriptions. Data source: ICASA, 2021

When comparing South Africa's telecommunication services performance with international countries in terms of internet speed, it became evident that the country is still lagging behind as observed in Figure 2.8. South Africa ranked 87 in fixed broadband speed and 55 in mobile broadband speed on an international platform.



	Thailand	Singapore	Hong Kong	Romania	Switzerland	South Africa
Fixed Broadband Speed (rank)	1	2	3	4	5	87
Mobile Broadband Speed (rank)	33	21	18	41	11	55
Fixed Broadband Download Speed (Mbps)	308,35	245,31	226,8	190,6	188,88	38,25
Fixed Broadband Upload Speed (Mbps)	260,86	231,58	212,26	130,43	121,1	26,3
Mobile Download Speed (Mbps)	51,75	66,82	72,13	45,93	89,89	38,95
Mobile Upload Speed (Mbps)	17,47	18,27	16,54	13,78	22,37	10,71



	Brazil	Russia	India	China	South Africa
Fixed Broadband Speed (rank)	50	48	65	18	87
Mobile Broadband Speed (rank)	75	90	129	4	55
Fixed Broadband Download Speed (Mbps)	78,1	80,86	53,9	158,66	38,25
Fixed Broadband Upload Speed (Mbps)	44,86	85,29	50,75	43,12	26,3
Mobile Download Speed (Mbps)	29,26	24,24	12,91	155,89	38,95
Mobile Upload Speed (Mbps)	10,38	10,41	4,97	30,67	10,71

Figure 2.8: Speed test benchmark. Data source: ICASA, 2021

2.4 Chapter summary

ICT developments have proved to be disruptive and the rate at which these digital transformations are being adopted by most first world economies is unprecedented. South Africa's National Planning Commission (2020), citing Smith and Reilly (2013), posits that "technological determinism, which assumes that technology is the factor which plays a central role on how our societies evolve and develop, is an overly reductionist and long since discredited manner of approaching socio-economic development”. In essence, ICT is designed and developed by humans for human use and unless a contextual and an all-inclusive approach is followed in understanding its current and future impact in South Africa, it may continue to be even more challenging for policymakers to address and reduce such high levels of unemployment.

CHAPTER 3

A LITERATURE REVIEW OF ICT DEVELOPMENTS AND EMPLOYMENT

3.1 Introduction

Automation and digitalisation of work, brought about by rapid developments in ICT, has been considered to be one of the most significant economic and societal movements in the world that will give rise to fundamental transformations in business, the nature of work, and societies within the next few years (Ford, 2015; Arntz *et al*., 2016). The advent of AI for decision-making and automation of production processes and the IoT that have enabled connectivity between humans and robotics, and big data analytics that have facilitated coordination within value chain systems among other things, are expected to create drastic transformations in the future world of work (Deloitte, 2018; Corfe, 2018). Manda and Dhaou (2019) point out that these ICT developments are characterised by expansion trends within all sectors of the economy with the intention of achieving smart institutions through intelligent service and production processes.

In as much as these transformations have the potential of eliminating many occupations and fundamentally altering many current professions, new industries with new occupations are likely to emerge with new ways of work (Hirschi, 2018:192). The rapid pace at which these developments are occurring, as they are bringing shifts in knowledge, wealth, and power, should be a major focus to researchers in order to ensure that all affected parties benefit from these technological changes (Xu *et al*., 2018:90). Therefore, to achieve a better understanding of the multifaceted complexities arising from this industrial era and the potential impact it may have on humanity, one needs to begin by examining similarities and distinctions from the previous industrial eras (Kapp, 2018; Balkaran, 2018).

3.2 Theoretical framework

3.2.1 Concepts and characteristics of ICT developments in industrial revolutions

In recent history, humanity has experienced four significant industrial revolutions that have disrupted societies' lives in unprecedented ways (Allam, 2020). For the purpose of this study, it is important to start by clearly defining the term "industrial revolution". According to Bonciu (2017) and Schwab (2018), this phrase alludes to an era of major transformation and industrialisation, which incorporates periods of disruption and transition within multiple spheres that affects the economy and society. Kapp (2018:19) defines an industrial revolution as "a period of accelerated structural change in the economy, involving a rapid rise in industrial output, and in factory-based activity based on major technological innovations". Allen (2015) further adds that these developments are as a result of humans evolving in knowledge and innovation, therefore, leading to transformations in economic activities, power dynamics, values and behaviours.

The notion of an industrial revolution can be viewed as a "continuous process of economic growth that would result in increased levels of both production and consumption for each successive generation as a direct consequence of industrialization" (Kapp, 2018:18). Deane (1979) suggested that industrial revolutions are mandatory for the development of an economy and the creation of wealth for its inhabitants. Several changes were also identified as characteristics of industrial revolutions within economic systems (Deane, 1979), and are listed as follows:

- Employment of newly developed technologies within production processes.
- Specialisation within an economic system focussing its activities on broader national and global markets.
- Larger, depersonalised and decentralised production units.
- Movements in labour from producing primary goods to manufacturing of goods and services.
- Scaling up the employment of capital resources to complement replaced human resources.
- The advent of new working and social classes.

According to Schwab (2018), what differentiates a revolution from an improvement is the fact that the changes brought about by a revolution are major and disruptive in nature and radically transforms global societies and economic systems. Therefore, these technological developments create a platform for the efficient production of additional goods and services, which in turn, has an effect on an economy's performance, the welfare and education of its participants, and the natural environment among others (Morathi, 2019). Due to the complex and incremental nature of an industrial revolution and the process by which it spreads to various parts of the world, Bonciu (2017) has suggested that researchers should refrain from relating to this phenomenon to a particular place or year, but to rather identify periods that parallel discoveries in science and technology that have had a major commercial effect.

Although many well-structured definitions of an industrial revolution have been provided, and the academic acceptance of these definitions is not unanimous. Some critics have persistently contested the existence of an industrial revolution, arguing that although the definitions have been broadly accepted by the general society, the notion of an industrial revolution has a historic flaw, it is not based on scientific grounding and it provides a deceptive impression of the dynamics that bring about changes in economic systems (Kapp, 2018). Taking this different point of view into consideration, it is important to point out that it would be oblivious to reject the existence of these continuous and rapid technological developments that have existed since the initial industrial revolution and the effects they have had, and continuing to have, on economies and societies in spite of the labelling or definitions given to them.

The initial industrial revolution took place in the 18th century, lasting almost a hundred years. This first revolution came about with the invention of the steam engine, which enabled farming societies to transition from the sole production of primary goods to new manufacturing processes and increased productivity (Xu *et al*., 2018:90). In this time period, the Western economies experienced consistently high levels of economic and population growth as a result of rapid industrialisation brought about by the employment of steam engines and improvements in the iron and steel manufacturing (Griffin, 2010; Kapp, 2018; Deane, 1979). Fuelled by the use of coal as the main source of energy, especially to power trains as the main form of transportation, the steel and textile industries took centre stage with massive inflows in capital investments leading to higher employment and outputs (Xu *et al.*, 2018:90). This era replaced a substantial segment of heavy manual labour with mechanical power signalling the development of new kinds of jobs and the requirement of new occupations, and new working environments, namely mechanised industries and factories (Kapp, 2018:20). Mechanised factories created numerous job opportunities, which attracted people to migrate from farms to the newly industrialised economic hubs (Brooks, 2018). According to Dietz (2008), it was during this time that the division of labour philosophy came to the fore. This notion was founded on the basis that the breaking down of production processes into separate tasks and assigning each labourer a particular task, led to an observation that output yields had increased more than when one labourer performed an end-to-end production task alone (Batt & Doellgast, 2005; Morathi, 2019:29).

An irreversible paradigm shift was therefore set as a foundation that supported subsequent industrial revolutions. Building on the First Industrial Revolution, was one which was characterised by the discovery of electricity and petrochemicals, which allowed for rapid industrialisation and mass production in the late 19th century (Peters, 2017:3). The discovery of electricity brought about drastic changes in the way people worked and lived and how factories operated. Rifkin (2012) points out that before the electricity era, petroleum lamps and candles were the only sources of light in factories and households therefore restraining activities to daytime. As electricity became commercially available, industries could continue production processes throughout the night-time. This industrialisation process produced the mechanical, electrical and chemical engineering industries, which resulted in the invention of internal combustion engines, interchangeable mechanical parts and continuous production lines, which gave rise to a boom of the automotive and aviation industry in the early 20th century and more division of labour (Morathi, 2019:30).

With the progression of mass production in the Second Industrial Revolution came about the introduction and application of scientific knowledge and management to industrial technologies and the work environment (Troxler, 2013; Morathi, 2019:30). This led to the centralisation of societies, which became very efficient and bureaucratic, bringing about automation in industries that were then able to produce goods and services with less human labour capable of working less hours making job losses inevitable (Xu *et al*., 2018; Mokyr, 2004; Voth, 2003). Blinder (2006), however, points out that the perception of work had to again shift to a more services-orientated paradigm as competition increased due to an increase in the production of goods. The shift resulted in the separation between the so-called “white-collar” and “blue-collar” occupation, where the former focussed on administrative and professional tasks while the latter did the labour-intensive work (Troxler, 2013). Those in the white-collar professions had typically higher levels of education as they had access to school and higher learning institutions and therefore professions in the field of accounting, engineering and medicine were introduced into the working environment (Barley & Kunda, 2001).

The mutual ground between the first two industrial revolutions was the modernisation of humanity by the ability to increase productivity and efficiency of the physical world for the use of land, capital and labour, which are still part of the factors of production to this day. However, in 1960 the Third Industrial Revolution, referred to as the information age, saw the implementation of information technology through the utilisation of “computers and the networking of computers to expand human activity from existing physical space to cyberspace” (Lee *et al.*, 2018).

This digital era saw further automation of electrical and mechanical systems by applying information technology and electronics for precision mechanics and advanced processing methods to computerise industries and create smart factories (Postelnicu & Calea, 2019; Gabriel & Pessl, 2016; Kapp, 2018:20). Rapid technological advancements in networked communication and computers through the invention of the internet allowed for easier information exchange, data processing and a reduction in the transactional costs gathering information (Rifkin, 2012). Economic growth was fostered by these new technological developments that brought about a new dimension into the world of work by changing traditional occupations to those that demand knowledge and the ability to solve more complex problems (Van Dam, 2017). Rifkin (2012) observed that, in as much as this industrial revolution automated many jobs, it also gave rise to numerous organisations creating millions of jobs globally.

When taking into consideration the above-mentioned industrial revolutions, human beings have constantly employed more advanced technologies in order to increase productivity and efficiency, and this phenomenon consistently transformed the position and importance of labour within the production process. Table 3.1 gives a summary, in chronological order, of the primary technological developments that drove the industrial revolutions.

Period	1760-1900	1900-1960	1960-2000	2000-present
Transition period	1860-1900	1940-1960	1980-2000	2000-2010
Energy source	Coal	Electricity, Oil	Nuclear energy, natural gas	Green energy
Main Goal	Mechanise production	Mass production	Automate production	Machines learning
Main Technical Achievements	Steam engine	Internal combustion engine	Computers, robots	Internet, 3D printing, genetic engineering
Main Developed Industries	Steel, Textile	Metallurgy, Auto, Machine Building	Auto, Chemistry	High Tech Industries
Transport Means	Train	Train, Car	Car, Plane	Electric Car, Ultra Fast Train
Relevant skills on the labour market	Practical trade crafts	Technical skills	Less laborious work, more logical thinking and creative design	Creativity

Table 3.1. Characteristics of industrial revolutions. Source: Prisecaru (2016:57)

Altogether, the first three industrial revolution developed over a period of roughly two centuries. According to Schwab (2016), today's transformations are not merely a representation of a prolonged Third Industrial Revolution but rather a distinct one – the Fourth Industrial Revolution. The velocity of current ICT developments and breakthroughs when likened to previous revolutions has no historical precedent as it evolves at an exponential rate (Kapp, 2018; Roser, 2017). Moreover, Asghar *et al.* (2020) cite that these transformations have brought about disruptions that affect all industries in every part of the world, heralding changes of entire systems of governance, management and production. Schwab (2016) further argues that:

> "*the possibilities of billions of people connected by mobile devices, with unprecedented processing power, storage capacity, and access to knowledge, are unlimited. And these possibilities will be multiplied by emerging technology breakthroughs in fields such as artificial intelligence, robotics, the Internet of Things, autonomous vehicles, 3-D printing, nanotechnology, biotechnology, materials science, energy storage, and quantum computing*."

According to Bonciu (2017), this ICT-driven era enables smart systems to integrate physical and virtual systems in order to customise goods and services with little to no human intervention. In the present day, the availability of infinite data and increased computing power has led to AI taking centre stage. This is being observed in the form of software that is able to invest, translate complex data or even discover new pharmaceutical drugs; algorithms that virtually assist customers and predict cultural interests; drone technology capable of delivering goods; and self-driving cars among others (Petrillo *et al*., 2018). Schwab (2016) also notes the interaction between the biological world and digital technology, where scientist and engineers are merging synthetic biological features with computational arrangements to introduce a symbiosis between micro-organisms, humans, products consumed and structures in which humans live and work. At the centre of these technological transformations is the objective to optimise on the interaction of innovations capable of creating an increase in economies of scale and profits (Dombrowski & Wagner, 2014). These innovative interactions can be observed in the vertical integration of all production process layers, and the horizontal integration of the entire value chain allowing for production flexibility and customisability (Kapp, 2018:23). Just as with the previous industrial revolutions, these ICT developments are destined to render many jobs obsolete, however, with the development of new industries, new skills and occupations will emerge (Hirschi, 2018). Therefore, organisations that constantly re-evaluate their technological capacity, production processes and skills-set to permit collaboration between machines and labour, are highly likely to maintain competitive advantage (Aslam *et al.*, 2016).

ICT disruptions may not be impacting all industries at the same rate or scale, nevertheless, it is evident from the above section that they are in fact already taking place. Although some of the effects have not yet manifested, others have already infiltrated mainstream society such as online shopping and banking, Uber, face recognition applications and Bitcoin. In order to have a glimpse of what form these new technological developments will take and how the labour market may be affected, it is essential to realise the interrelatedness, complexities, depth and velocity of these ICT developments as indicated in Figure 3.1 and 3.2.

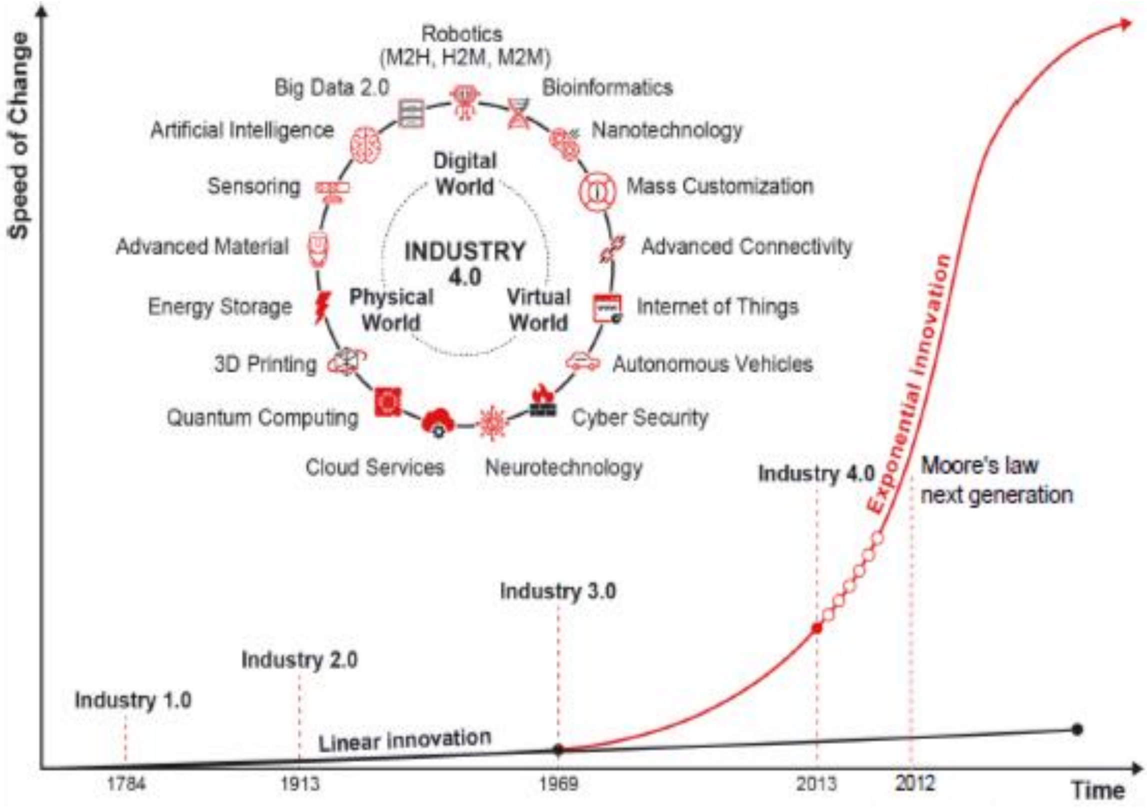


Figure 3.1: ICT development interconnectedness and rate of change. Source: von Scheel (2016:4)

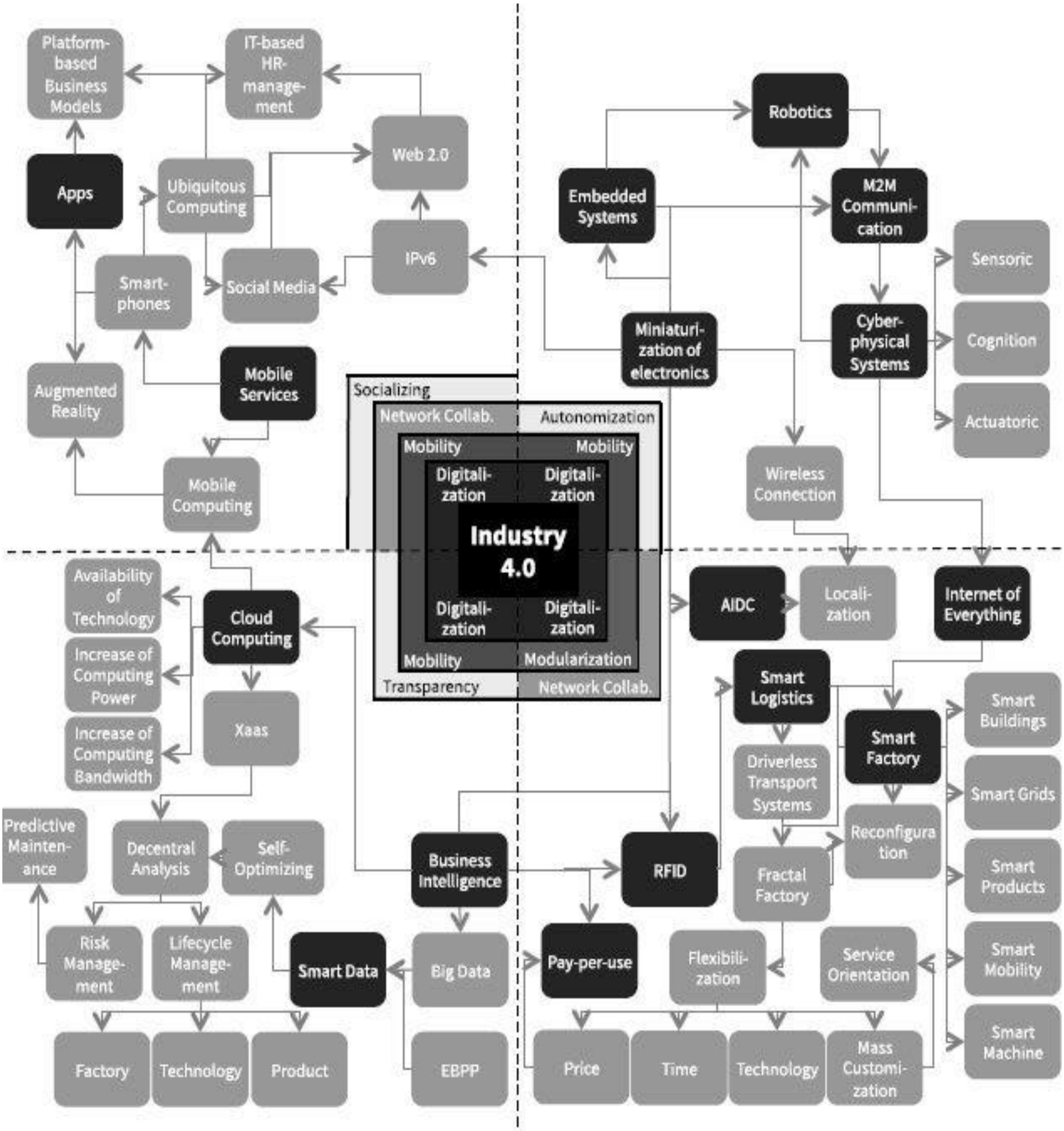


Figure 3.2: Interrelatedness and complexities of ICT developments in the Fourth Industrial Revolution (4IR). Source: Pfohl et al. (2015:41)

It is evident from above figures that there are numerous emerging ICT developments that will undeniably transform all industries, societies and the future world of work. Examining and illustrating all these individual technological advancements is not the focus of this study but were highlighted only to emphasise the unprecedented dynamics of this ICT era in relation to its predecessor and to lay a foundation on which to assess how employment may be influenced by these developments.

3.2.2 Employment

Broadly speaking, employment is when people earn a wage or salary for providing a service to an organisation or profession in which this employment could either be labour-intensive – production activities produced by human labour – or capital-intensive – production from the use of technology and machinery (Dornbusch *et al*., 2014). Unemployment on the other hand consists of a broad and narrow definition. The narrow definition according to Barker (1992:81) is as follows: *"*The unemployed are persons who, being fifteen years and older, were not in paid employment or self-employed i.e., did not work for five or more hours for a wage or salary or for profit or family gain during the seven days preceding the survey; were available for paid employment or self-employment during the reference week (the seven days preceding the interview); and took specific steps during the four weeks preceding the interview to find paid employment or self-employment; or had the desire to work and to take up employment or self-employment."

Posel *et al.* (2012:2) simplify the narrow definition of unemployment as "a situation in which people are able, willing and actively looking for work but cannot find jobs". However, the narrow definition had a shortcoming as it did not take into account the unemployed people who have become discouraged from actively seeking employment and are no longer taking the necessary steps (Bangane, 1999:7). Provisions were later made to relax the requirements and include what is now known as the broad definition (Barker, 1992:83). The broad definition of unemployment is said to be "those (aged 15-64 years) who were not employed in the reference week, and were available to work but did not look for work either because they were discouraged from looking for work or did not look for work for other reasons other than discouragement" (Stats SA, 2020:12)

De Long and Olney (2009) state that a country's growth and development can be closely linked to its level of employment and labour efficiency as this is what differentiates wealthier and productive economies from others. Manete (2018) explains labour efficiency as “the ability of the labour force to use the production resources with which the market functions”. The production of goods and services is guided by their demand, which follows that an increase in the demand for consumption of those goods and services will assumedly prompt the business to increase production capacity in order to meet the demand and as a result, employment is created (Manete, 2018:15). In addition, as economic growth increases, so does labour through a surplus labour market and as a result increased employment becomes the end result.

In a developing country like South Africa, challenges of declining economic growth in recent years have resulted in a lack of sustained job creation, with unemployment remaining the country’s key issue (Faulkner *et al.*, 2013). This lack of sustainable employment has consequently worsened the state of poverty and inequality, which were inherited from the colonial era, due to the country’s inability to reach its macroeconomic objective (Leibbrandt *et al*., 2010). In the first quarter of 2021, the narrow unemployment rate stood at 32.6% (with the youth accounting for the most percentage at 24.4%), the highest ever recorded in South Africa, while the broad unemployment reached 43.2% (Stats SA, 2021). Okun (1962) asserts that there is a negative relationship between economic growth and unemployment, and therefore employment will result with an increase in GDP. To obtain a better understanding of the employment dynamic, this section explores economic theories of employment, namely the Keynesian theory of employment, the classical theory of employment, and the Okun’s law.

3.2.2.1 Classical theory of employment

According to Schumacher (2012:58), classical economists had the belief that all labour resources are always entirely employed in an economic system. This full employment philosophy refers to a scenario where the labour force that is able and willing to accept employment at the current wage rate will get hired (Manete, 2018:25; Patinkin, 1948). Classical theorists hold the idea that full employment is the level of employment that the economy always returns to, and is inclined to remain at, in the long-run. In such a situation, the supply of labour is equal to the demand for labour signifying the absence of unemployment and those who have no employment are doing so voluntarily (Tobin, 1995:33). Manete (2018:25), echoes the laisser-faire theory by asserting that the interference of government institutions with the markets results in a disequilibrium, a sentiment held by classical economist that when private organisations and governments interfere with the markets, unemployment is created (Pritchard, 1985:48).

Say's law, on which the classical theory of employment is founded, states that supply creates its own demand (Manete, 2018). In other words, when companies supply goods and services, income gets spent and in turn households are rewarded with income in the form of wages for their factors of production, which then spends that income to consume more goods and services (Manete, 2018:25; Baumol, 1977:146). This represents the simple circular-flow model where companies utilise their entire resources (owned by households) whereby the costs of these inputs are the wages/income that households use to purchase all outputs produced by the supplier. Moreover, Foley (1985;183) adds that whenever a good or service is produced, a market value equivalent of that good or service is created. A production function expressing these relationships from a classical theory of employment can be written as:

$Y = f(K,T,L)$

Where Y = Total output
K = Capital
T = Technological knowledge
L = Labour

When production capacity of a company increases, output also increase and consequently the number of labourers also increase. On the contrary, Keynes argued that household income received in the form of wages will not all be spent on consumption of goods but will be saved and therefore the supply of goods and services produced will be greater than the demand (Mastrianna, 2013:198). As a result, the producer is compelled to decrease production and resources employed in the production process, and when the economy's resources are employed below their full level, the output's equilibrium level then falls below the natural rate (Mastrianna, 2013:198). Moreover, a company's inability to sell its production output as determined by its supply curve will decrease their demand for labour resulting in a disequilibrium and eventually cyclical unemployment – unemployment caused by a low demand for services and goods (Manete, 2018:29; Mohr & Fourie, 2008).

3.2.2.2 Keynes' theory of employment

Keynes argued against the self-correcting free markets economic system, held by the classical school of thought, and said that levels of employment were not a function of the price of labour but rather a function of aggregate demand (Keynes, 1936). In his *General Theory of Employment, Interest and Money*, he defines full employment in terms of two variables, namely aggregate demand and labour market functioning. Firstly, it is the maximum level of aggregate demand, which is a "situation in which aggregate employment is inelastic in response to an increase in the effective demand for its output"; and secondly "the equality of the real wage to the marginal disutility of employment" (Rivot, 2012; Keynes, 1936). It is important to note that Keynes' definition of full employment does not mean the absence of unemployment as he alludes to the fact that the labour market has imperfections such as voluntary and frictional unemployment (Rivot, 2012; Leijonhufvud, 1968: 93; Keynes, 1936)

According to Keynes' theory, aggregated demand (measured as the sum of government, businesses, and household spending) is the most significant driving force behind any economy (Jahan et al, 2014:53). This theory further emphasises that free markets do not have self-correcting measures that equilibrates to full employment. He held that unemployment was a normal state of an economic system and believed that governments (through active fiscal policy) needed to intervene in order to stimulate and improve employment levels and with a country's available resources, its level of output is what actually determine employment (Galí, 2013:3). Keynes advocated that employment is determined by the aggregate demand of goods and service, or simply put, a rise in the demand for goods and services in a country will raise employment levels. Therefore, insufficient aggregate demand may lead to lengthy periods of high levels of unemployment. Jahan *et al.* (2014) state that "An economy's output of goods and services is the sum of four components: consumption, investment, government purchases, and net exports (the difference between what a country sells to and buys from foreign countries). Any increase in demand has to come from one of these four components". However, during periods of economic downturns, demand is dampened due to a reduction in spending as consumer confidence is eroded. This then leads to firms spending less on investment in response to low demand for their goods and services therefore putting the pressure on government to increase output and avert job losses (Jahan *et al.*, 2014:53).

3.2.2.3 Okun's law

The relationship between employment and economic growth has been widely tested by economist since its introduction by Arthur Okun (Fatia & Bankole, 2013). Okun proposed that there is a positive relationship between employment and economic growth (Manete, 2018). He postulated that a percentage change in employment will result in a 3% change in economic growth, therefore, explaining how severely GDP could be influenced by high levels of unemployment (Lee, 2000:331). Okun's law was hypothesised on the school of thought of full employment, while keeping other growth determinants constant, suggesting that a country's economic growth is determined by the labour resources employed in the production process, meaning that economic growth will increase as production capacity increases (Manete, 2018).

3.2.3 Employment and ICT

Every major breakthrough in technology fuelling the industrial revolutions, from the advent of assembly lines and the production of automobiles, to personal computers and smartphones, have elevated concern about employment. Nonetheless, with every industrial revolution, market economies were generally capable of continuously generating relatively enough employment for their labour force (Autor, 2015). Although ICT developments have been observed to have a direct reduction in labour demand, Spiezia and Vivarelli (2002) are of the view that several automatic market adjustments are triggered which then compensate for the reduced demand in labour. In an attempt to understand the forces at play between ICT and employment, it is helpful to differentiate between two important concepts: product innovation and process innovation. Product innovations lead to the commercialisation of new products and services such as smartphones, self-driving cars and social apps (e.g., WhatsApp), whereas process innovations result in increased productivity such as automated inventory management systems and online banking systems (OECD, 2016:6).

An increase in overall productivity through process innovation occurs as a result of the ability of a company to produce a specific number of goods and services utilising less labour and therefore potentially resulting in possible technological unemployment. Meanwhile, in a competitive market economy, process innovation also reduces the unit cost of production, which translates into reduced prices therefore stimulating more demand for the goods and services (Sabadash, 2013). This increased demand creates more production and therefore employment and this is referred to as compensation through a decrease in prices (OECD, 2016:7).

3.3 Empirical studies

The impact on the creation or destruction of employment by ICT has over the past decades attracted extensive attention from all economic and social spheres (OECD, 2016:10). ICT developments play an important role in the labour market due to the fact that while they render many jobs obsolete, they also create new job opportunities from the development of new product and service markets (Kilicaslan & Tongur, 2019:1053).

According to Kilicaslan and Tongur (2019), the impact of ICT on employment can theoretically be approached from two main dimensions: the compensation and substitution mechanisms (Sabadash, 2013:8). The substitution mechanism speaks to the destructive effect on employment emerging from the improvement of technology by traditional industries since new technologically advanced processes require less labour (OECD, 2016). On the contrary, the compensation mechanism postulates that the "labour-saving effect of technological progress may be compensated by market-orientated indirect effects so that underlining technological change leads to employment generation in the long-run" (Kilicaslan & Tongur, 2019:1053; Sabadash, 2013:8). As new technologies are introduced in the production process, production cost become reduced and new investment are generated resulting in new job opportunities. Technological transformations induce the development and commercialisation of new goods and services and therefore new jobs (European Commission, 2016).

There are numerous empirical studies on the effects of ICT innovation on employment, however, there is no unanimous consensus on the direction of ICT's creative or destructive effect on employment (Kilicaslan & Tongur, 2019:1054). The following section discusses some of the empirical studies on the employment effects of technological advancements in recent years.

3.3.1 ICT innovations and employment

During the 1990s and early 2000s, European countries experienced a decline in employment within the manufacturing industry largely as a combination of the introduction of technologically innovative processes, increase wages and a weakened demand (Bogliacino & Vivarelli, 2011). According to Pianta and Bogliacino (2010), losses in employment happened mainly in large organisations, among employees with low levels of skills and in capital-intensive and ICT-driven sectors of the economy. On the other hand, industries that showed an increasing growth in demand – those in which process innovation was dominated by product innovation – had a higher concentration of job creation (OECD, 2016:10). Product innovation has been confirmed to have a positive effect on employment levels while the impact of process innovation revealed to have both negative and positive effects. Harrison *et al.* (2008) cited a string of research work on European Community Innovation Survey data and found that most losses in employment occurred mainly in non-innovating companies whereas those that introduced new products drove employment growth. The study found a negative effect of process innovation on employment in the German manufacturing industry alone.

The same model was run by Hall *et al.* (2008) on a number of manufacturing companies in Italy between 1995 and 2003 and found that there was in fact a positive relationship between product innovation and employment while the effects of process innovation on employment were insignificant. Another study by Lachenmaier and Rottmann (2011) used a similar model on data from manufacturing companies in Germany, over a period of 10 years (between 1982 and 1992), to estimate a "dynamic employment equation", and also found a positive relationship between both process and product innovations and employment. Bogliacino *et al.* (2011) examined data from 677 services and manufacturing companies in Europe between 1990 and 2008 and found that expenditure on R&D positively affected employment, however, not in traditional manufacturing but rather in high-tech manufacturing (OECD, 2016). Coad and Rao (2011) analysed a "composite innovativeness index" dataset (which included patents and R&D) from 1963 to 2002 of high-tech manufacturing companies in the United States (US) and concluded that a positive relationship exists between R&D and employment.

Evangelisti and Vezzani (2011) took a more dynamic approach and examined the effects all forms of innovation (product, process and organisational) on employment and found that employment is indirectly affected by improvements in performances, which result in increased sales and additional jobs. Therefore, strategies geared towards innovation, which is characterised by a blending of organisational, process and product innovations have indicated a robustly positive effect on employment, however, with the exception of process innovations that showed a negative direct impact on employment observed only in manufacturing companies (OECD, 2016; Evangelisti & Vezzani, 2011).

Rotz *et al*. (2019) investigated the restructuring of labour in the North American agriculture industry as a result of mechanisation. In collecting their data, they focussed on "precision-tech, robotics, sensors, data software systems, drones and mobile phones as opposed to communication and transparency technologies like RFID chips or social media platforms", and analysed it using labour-saving technology and automation as their main digital agriculture component. Their conclusion was that although automation on agricultural production processes have led to an overall loss of employment among low-skilled employees, those unskilled labourers who are still employed face a greater effect of exploitation.

Biagi and Falk (2017) aimed to examine the correlation between employment and access to broadband from a country-level to organisational-level dataset of European countries. This was after their literature study observation of Atasoy (2013) and Kolko (2012) that found that broadband access had a positive impact on employment from analysing country-level data in the US between 1999 and 2007, whereas Stefano *et al.,* (2014) found no effect of broadband availability on employment growth in the United Kingdom using an organisational-level dataset. After analysing this literature, Biagi and Falk (2017) focussed on labour demand and e-commerce activities, using data from ten European countries, particularly broadband internet access, websites and ERP systems. They, however, found no evidence that supported their initial hypothesis of ICT applications negatively impacting employment, but rather there was no impact on employment by those ICT enablers.

Severgnini (2009) conducted an analysis in order to determine the different results by various studies using the following ICT measures: (a) ICT's contribution towards overall productivity; (b) Investments in ICT to output ratio; and (c) ICT measurements by a time trend. The measures gave inconsistent results as summarised below:

- ICT's contribution towards overall productivity – shows a negative impact in both the long and short-run.
- Investment in ICT to output ratio – shows varied effects on employment.
- ICT measurements by a time trend – shows a negative effect in the short-run but a positive effect in the long-run.

Indirect effects of ICT on employment have also been widely estimated using the ICT employment multiplier which measures the total growth in employment created by one additional employment in the ICT sector (OECD, 2016). In essence, this multiplier indicates how many jobs within the economy are created as a result of one new job in the ICT field. A study by Kats (2012) examined the broadband employment multiplier from numerous studies and found a variation from as high as 3.6 to 1.92 in the US and Germany, respectively. Moretti (2012) claims that the employment multiplier in the ICT industry can be as high as 5, meaning that one job created in the life sciences, technology, and software industries in the US will indirectly result in five new jobs in the economy, two high-skill professions such as medical practitioners and advocates and three low-skill trades such as cashiers, hair-stylists and waiters. In contrast, Mandel and Scherer (2012) estimated a relatively lower multiplier of 1.5 after analysing employment multipliers related to the app development industry (looking specifically at Facebook).

Theories in economics do not have an official model on the impact of ICT on employment due to the different findings in empirical studies and therefore these extensively heterogeneous results are conveniently categorised into the technological "pessimistic" views (the so-called technophobes) and the technological "optimistic" views (the technophiles) (Martinez-Corcoles *et al.*, 2017; OECD, 2016). Moretti (2012) with an estimate of the high-tech employment multiplier of 5 can be categorised as a technophile. These people enthusiastically accept all technological developments in a positive way and view ICT enablers as a means to combating societal issues and improving the way of work and life in general. According to Caliskan (2016), this category has observed the same emotional relationships that people have towards each other now increasingly making its way between humans and machines, and therefore making it impossible to reject the materiality of ICT. However, this idea that humans are powerless in resisting ICT infiltration may hinder the realistic assessment of its influence on employment (Uche, 2011).

Technophobes, on the other hand, are those who have an “irrational fear or anxiety caused by side effects of advances in technology” (Osiceanu, 2014). They hold a negative view towards ICT advancements despite its inevitable infusion into the way of work and daily living. Frey and Osborne (2013) belong to this category of technological pessimists. They are of the view that within the coming decade, about 50% of generally defined occupations could be at risk of being automated leading to market polarisation. This phenomenon was also observed by Autor and Dorn (2013) after analysing changes in employment, between 1980 and 2005, by skill percentile and wages and found that employment in high-skill occupations increased while it remained stagnant and, in some cases, even decreased in the lower and middle-skill occupations.

Butler-Adam (2018) argues that even after such numerous advancements in ICT, a major section of those concepts and the impact they may have on employment are still theoretical and speculative resulting in uncertainty. Nevertheless, it is evident that there are major transformations in occupations and the world of work with the introduction of ICT innovations in the workplace.

3.4 Chapter summary

Literature indicates that there is no consensus on the whether ICT will have an over all positive or negative effect on employment. This could be due to a lack of empirical studies conducted on this topic to provide positivistic analysis using analytical and statistical methods, and therefore the need to fill this gap by conducting this study.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Introduction

Theoretical and empirical literature on the impact of ICT and employment in South Africa were reviewed in Chapter 3 of this study. The literature review suggested that a relationship exists between ICT and employment levels. In the case of South Africa, limited empirical studies have been conducted with regard to the impact of ICT developments on levels of employment signifying the existence of a gap in knowledge in the context of this country. In that regard, this chapter explores econometric models in an attempt to fill the gap by looking at the following empirical objectives:

- To detect the direction of causality between ICT and employment in South Africa by focussing of data spanning from 1990 to 2020.
- To investigate the impact of ICT on employment in South Africa and analyse the extent to which these ICT developments have had an effect (whether positive or negative) on the labour force.
- To determine the spill-over influences of ICT development and employment in South Africa.

This chapter provides a clear and comprehensive view of the methodological approach employed in this study, a clear description of the variables used, collection of data, and the econometric model that was utilised. For example, the Granger causality test was used to test the causal relationship between ICT developments and employment, while the estimation of the short and the long-run relationship between the different variable was conducted using the error correction model. In addition, an explanation and motivation on the use of the unit root and diagnostic tests are provided.

4.2 Econometric models

A functionalist approach to economics was chosen in this study's methodology based on quantitative methods. This approach has been determined to operate well in investigations relating to social and economic paradigms when attempting to comprehend economic attributes and their relation to particular systems (Camel, 2018). The fundamental element in this study is to employ a dynamic model capable of accurately and consistently examining behavioural characteristics of a system over a period of time (Yuai, *et al.,* 1999:1661). In order to analyse the data towards achieving the empirical objectives aimed at shedding light on the impact of ICT on employment, a number of econometric models were explored using EViews Version 11 as the econometric tool of choice. These models include the unit root test, Johansen cointegration test, the Granger causality test, the error correction model (ECM), and the VAR model (Asteriou & Hall, 2011).

4.2.1 Unit root and stationarity test

When analysing time series data, Gujarati and Porter (2008) state that it is necessary to conduct a stationarity test to avoid obtaining a spurious regression in which the variables are independent and non-stationary. Non-stationary time series data result in an invalid classical regression analysis where the results have no meaning and are uninterpretable (Asteriou & Hall, 2011). A series with a variance, constant mean and auto covariance for every specified lag is said to be stationary and this can be tested using the following equation (Brooks, 2008:318; Charemza & Deadman, 1992:128):

$$X_t \approx \mathrm{I}\ (d) \qquad (4.1)$$

Where d represent the order of integration that denote the number of units roots in a series or how many differencing are needed to get a variable stationary (Manete, 2018). For instance, a series X_t is stationary when d = 0 and it is integrated of order zero I(0) (Asteriou & Hall, 2011). Therefore, the main aim of a stationarity test is to stabilise the series variance, constant mean and auto covariance over a period of time (McCamel, 2018). Several techniques are used to detect unit roots including the augmented Dickey-Fuller (ADF) unit root test, Phillips-Perron (PP) unit root test, Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) stationarity test, Leyborne-McCabetest test, Kahn and Ogaki test, as well as cointegration regression Durbin-Watson (CRDW) test (Asteriou & Hall, 2011; Ogbokor, 2015). The most commonly used method is the ADF unit root test, which according to Johansen (1988) is much simpler in nature. However, Cheung and Chinn (1997) point out that due to the ADF unit root test's sensitivity to structural breaks and samples size distortions, assessing such data may result in unreliable results. Ageli (2013) therefore suggests assessing the robustness of the ADF unit root test results by estimating the PP unit root test.

Therefore, the first step in this study was to conduct a stationarity test of the variables using the ADF and PP unit root tests. Furthermore, these stationarity tests were conducted in three differentiating steps i.e., firstly with only a constant, then with a trend and finally with a tend and intercept.

4.2.1.1 Augmented Dickey-Fuller unit root test

Developed by David Dickey and Wayne Fuller in 1979, the ADF unit roof test uses intercepts and trend, in level, first and second difference. This augmented version was developed to included extra lagged terms of the depended variable so as to eliminate autocorrelation (Asteriou & Hall, 2011). Dickey and Fuller (1981) presented the ADF unit root test's hypothesis testing as:

H_0: Unit root in the series (non-stationary)

H_1: No unit root in the series (stationary)

In order to reject the null hypothesis, the ADF results should be statistically significant at 1% or 5% significance level, therefore concluding that the data are stationary. The rejection of H_0 signifies the acceptance of H_1 on condition that the p-value is statistically significant (McCamel, 2018). In the event where the H_0 of unit root in the series was not rejected due to the p-value not being statistically significant at 1% or 5%, the ADF unit root test was re-calculated according to the three differentiating steps until H_0 was rejected (Asteriou & Hall, 2011).

Once the variables have been regressed, they can be able to accommodate the effects of the lag series by following the autoregression of the order (*p*) based on the estimated regression equation 4.2.

$$\Delta\gamma_t = \alpha\gamma_{t-1} + \delta x_t + \beta_1\Delta\gamma_{t-1} + \beta_2\Delta\gamma_{t-2} + ... + \beta_n\Delta\gamma_{t-n} + \mu_t \qquad (4.2)$$

Where:

$\Delta\gamma_t$ – First difference of γ_t (i.e., $\gamma_t - \gamma_{t-1}$)

β and δ – Parameters to be assessed;

x_t – Exogenous variables;

μ_t – White noise (or Error term); and

γ_{t-n} – Variables that rectify serial correlation errors

From this equation, the ADF unit root null hypothesis (H_0) is generated to assume the presence of unit root, i.e., α = 0, while the alternative hypothesis (H_1) assumes the absence of unit root, i.e., α < 0 as briefly indicated:

H_0: $\alpha = 0$

H_1: $\alpha < 0$

The null hypothesis of the ADF test is rejected when the coefficient (α) is less than zero implying that the variables do have a unit root, therefore accepting the alternative hypothesis indicating stationarity of variables (Asteriou & Hall, 2011). If the coefficient is equal to zero, the null cannot be rejected and therefore the variables that are non-stationary will undergo the differentiating steps to a point where they reach stationarity.

4.2.1.2 Phillip-Perron unit root test

The PP unit root test is very similar to the ADF unit root test with the fundamental difference being the manner in which each manages serial correlation (Asteriou & Hall, 2011). However, the hypothesis testing framework followed by the PP test is similar to the ADF test and therefore the two tests generally produce the same results. The ADF approach utilises parametric autoregressions to estimate the structure of errors, through the introduction of lags of γ_t as repressors so as to address serial correlation, whereas the PP approach disregard all serial correlations through the refinement of the t-statistic (McCamel, 2018). Therefore, the PP tests are basically modifications of the ADF t-statistic taking into consideration the less restraining characteristics of the error processes (Asteriou & Hall, 2011). The PP unit root test process can therefore be expressed as follows:

$$\gamma_t = \alpha\gamma_{t-1} + \delta x_t + \mu_t \quad (4.3)$$

$$\Delta\gamma_t = \beta_0 + \beta_i D_{t-i} + \mu_t \quad (4.4)$$

Where:

t – trend

β_0 – constant

D_{t-I} – The deterministic trend component

μ_t – I(0) with zero mean

When $\beta_i = 0$, the variables are said to have unit root implying non-stationarity, whereas if $\beta_i < 0$, this in an indication of the absence of unit root meaning the variables are stationary.

4.2.2 Model selection criteria

The first step when analysing time series data is to run unit root tests to ensure that the variables do not contain unit roots. Selecting the appropriate methodology for analysing time series data is very important as the wrong choice of method may provide unreliable and biased results. The method selection used in analysing time series is primarily determined by the unit root results whereby methods used to analyse stationary data should not be used to analyse non-stationary data (Shrestha & Bhatta, 2018:75). When the variables under analysis are stationary, the ordinary least square (OLS) is applicable and the vector autoregressive (VAR) models are favoured when all the variables are not stationary at level and no cointegration exist (Asteriou & Hall, 2011). However, if the variables are non-stationary, or of mixed type (i.e., others are stationary while some are non-stationary), a more appropriate method is required to examine the relationship between variables (Shrestha & Bhatta, 2018:75). Figure 4.1 summarises the approach as follows:

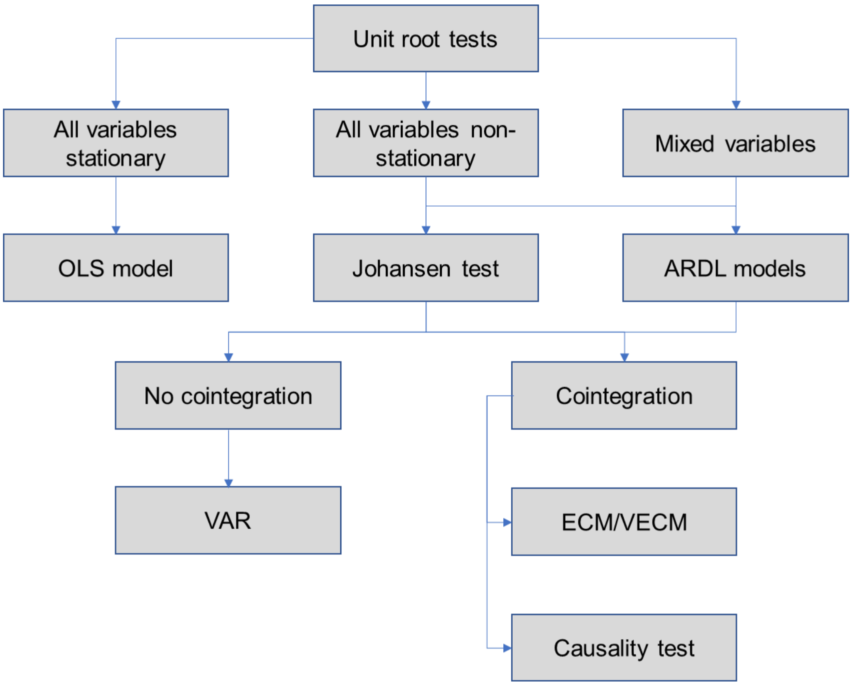


Figure 4.1: Method selection approach for time series data. Source: Bhatta and Shrestha (2018:76)

Variables that are non-stationary can be transformed into stationary data by applying first difference, however, modifying non-stationary data by differencing may result in the long-run trend/relationship of the variables being lost (Asteriou & Hall, 2011).

4.2.3 Ordinary least square method

After having conducted unit root tests and the results indicate that all variables are stationary, the OLS method may be utilised to estimate the relationship between the chosen variables. In this method, a bivariate linear regression model is then estimated using the following equations (Asteriou & Hall, 2011):

$$Y_i = b_i + b_2X_i + e_i \qquad (4.5)$$

[also written in the form;]

$$e_i = Y_i - \hat{Y}_i = Y_i - b_i - b_2X_i \qquad (4.6)$$

This model indicates that the residuals (e_i) are basically the difference between the Y_i (the actual values) and $\hat{Y}_i$ (the estimated values) while choosing b_i and b_2 to minimise the residual sum of squares (Gujarati, 1995). Stationary data do not need differencing, however, by applying differencing only one time, non-stationary data can be transformed into a stationary time series and said to be integrated of order one I(1). Additionally, differencing the non-stationary data two times is said to be integrated of order two I(2). It is crucial to note that utilising the OLS model on differenced data will indicate short-run changes only and completely neglects the long-run relationships (Shrestha & Bhatta, 2018:77).

4.2.4 Vector autoregressive model

The vector autoregression (VAR) model is a multivariate time series model capable of relating present observations of a particular variable with historic observations of itself and also of other variables in the model (Aptech, 2021). The VAR model assumes that all the regressors are endogenous and therefore does not require variables that are exogenous. This model can only be employed when the variables are integrated of the same order (Manete, 2018:75). Firstly, unit root tests need to be conducted to test for stationarity and to examine if cointegration between variables exist in order to proceed in estimating the VECM. The VECM refers to the velocity and time it takes the dependant variable to go back to equilibrium after-shocks have been imposed on the independent variable (Manete, 2018). Brooks (2014) suggests that in order to obtain the best results, an appropriate lag length needs to be determined, and therefore this VAR model was constructed using the lag that would produce the best results. A basic VAR model involving two variables X and Y with only one lag can be written as follow:

$$Y_t = \delta_1 + \theta_{11} Y_{t-1} + \theta_{12} X_{t-1} + \mathcal{E}_{1t} \qquad (4.7)$$

$$X_t = \delta_2 + \theta_{21} Y_{t-1} + \theta_{22} X_{t-1} + \mathcal{E}_{2t} \qquad (4.8)$$

Where:

Y_t and X_t are the independent and dependent variables, and $\mathcal{E}_{1t}$ and $\mathcal{E}_{2t}$ are uncorrelated error terms.

According to Shrestha and Bhatta (2018:77), selecting appropriate lag lengths is critical and the ideal number can be selected using criteria such as the Hannan-Quinn criterion (HQC), Bayesian information criterion (BIC), Akaike information criterion (AIC), and Schwarz information criterion (SIC). Using the correct lag order prevents the standard terms from being negatively influenced by heteroscedasticity, autocorrelation and non-normality (Nkoro & Uko, 2016:82). Manete (2018) states that "when few lag lengths are employed, the regression residuals do not behave like a white noise process and when many lag lengths are employed, the strength of the test to detect a unit root will be reduced". The econometric tool employed in this study (Eviews 11) has an automatic function capable of choosing the suitable lag order and therefore minimising the likeliness of error in this regard.

4.2.5 Johansen cointegration test

Employing OLS or VAR methods on non-stationary time series data are more likely to generate spurious results, meaning that the estimated regression results could be displaying a strong relationship between the variables whereas there is no correlation between them (Engle & Granger, 1987). Conversely, there could exist a long-run equilibrium relationship between variables even through deviation from the equilibrium is observed in the short-run (Shrestha & Bhatta, 2018:77). This prompted Engel and Grander (1987) to develop a cointegration method capable of examining relationships between variables that are non-stationary of which Johansen (1988) later improved by addressing discrepancies in their model.

This study conducted the Johansen cointegration test due to its usefulness in testing for cointegration of several non-stationary time series data. In contrast to the Granger causality test, the Johansen cointegration test permits multiple cointegration relationships while avoiding the problems generated by errors that are carried along various steps. In order to determine the cointegration relationship between the dependent and independent variables using the Johansen cointegration test, the variables need to firstly be tested if they are I(0) or I(1) (Naidu *et al.*, 2017). The study then continued with the Johansen cointegration test when all the variables were found to be integrated of order one I(1), with the general equation captured as follows (Asteriou & Hall, 2011):

$$Z_t = A_1 Z_{t-1} + \ldots + A_n Z_{t-n} + Bx_t + \mathcal{E}_t \tag{4.9}$$

Where,

Z_t = vector for the I(1) dependent and independent variables,

x_t = vector of the non-random variables

$\mathcal{E}_t$ = error correction term

4.2.6 Error correction model

When the variables are integrated of order one and cointegration relationship is determined between the variables, the ECM can therefore be examined.

4.2.7 Granger causality test

An important factor to remember when analysing time series data is the interest of determining whether changes in one of the variables causes changes in the other variable and identifying the direction of the causality (Markova, 2016). The Granger causality test was employed to examine the impact of ICT developments on employment and their statistical causality. This test is used to determine the existence of a causal relationship between variables. The Granger causality approach tests whether the dependent variable is caused by the independent variable or vice versa and to what extent can the current independent variable be described by the historic values of the dependent variables (Asteriou & Hall, 2011). Markova (2016) states that the "rationale for testing the causality involves implementing F-tests to investigate whether lagged values of a variable Y provide any statistically significant information relative to variable X in the existence of lagged X values". In essence, the Granger test validates the usefulness of one variable to forecast another, and therefore variable Y is said to Granger cause variable X if it has proved useful in forecasting variable X. The causal relationship is estimated by the following bivariate model (Vazakidis & Adamopoulos, 2011:145):

The test hypothesis can therefore be stated as follows:

$\boldsymbol{H_0}$: Employment does not Granger cause ICT, if F_c < critical value of F.

$\boldsymbol{H_1}$: Employment does Granger cause ICT, if F_c > critical value of F

and

$\boldsymbol{H_0}$: ICT does not Granger cause employment, if F_c < critical value of F.

$\boldsymbol{H_1}$: ICT does Granger cause Employment, if F_c > critical value of F

4.3 Definition of variables and data sources

4.3.1 Data source

Secondary data were utilised to examine the interrelationship between advancements in ICT and the effects they have on employment in South Africa. In the case of labour market statistics (i.e., employment, labour force, and education levels), quarterly labour market time series data were collected from the Statistic South Africa (Stats SA) database and pooled to generate an annual dataset spanning from 1990 to 2020 due to data availability. Data on ICT development were collected from the World Bank's World Development Indicator (WDI) database to create a mean annual ICT index composed of mobile and fixed voice and internet subscriptions, and internet penetration/usage. The availability and reliable data have limited the study to a period from 1990 to present day – of which this study's dataset was capped at 2020. Data for the GDP variables were obtained from the South African Reserve Bank (SARB) and the WDI database, whereby this variable is determined using real values adjusted seasonally at constant 2010 prices.

According to Brooks (2014), in order to reduce residuals for datasets with huge variables and to obtain meaningful coefficients, this data had to be transformed into natural logarithms in order to achieve stationarity.

4.3.2 Definition of variables

It is important to consider the fact that the labour market performance and development are based on various economic models when analysing the effects of ICT on employment. The classical model, which is founded on the idea of full employment with an overall balance between labour demand and supply, advocates that unemployment is only a momentary effect of the labour market (Serena, 2016:206). The classical economists are of the view that there exist only natural unemployment whereby gaps between labour demand and supply can be regulated through wage increases. Conversely, the Keynesian model argues in favour of an unbalanced labour market in which the "the wage is not flexible, but is fixed and there may be an overall balance in the case of underusing the labour, leading to its underemployment, therefore requiring state intervention to realise full employment" (Serena, 2016:206). It therefore becomes clear that with current ICT developments and their potential substitution of labour, the assumption of wage rates as the only factor determining the labour market can therefore be disregarded (Mncayi & Shuping, 2021:4). To achieve a broader view of the impact on employment, other variables had to be considered in the analysis.

This study focussed on employment levels as the dependent variable while the determinants form the independent variables. These determinants comprise ICT development, income, GDP, levels of education in the form of adult literacy, labour force, and capital stock (Table 4.1).

- Employment – A measure of the total segment of the population who are employed represented as a ratio of the working-age population.
- ICT development – The mean ICT index that comprises mobile and fixed voice and internet subscriptions, and internet penetration/usage.
- GDP – Real GPD as a proxy of economic growth measured using values adjusted seasonally at a yearly rate at constant 2010 prices.
- Income – The wage rate in terms of GDP (a benchmark on which a country's performance is evaluated).
- Levels of education – Measured using the gross enrolment ratio which is "the ratio of total enrolment, regardless of age, to the population of the age group that officially corresponds to the level of education shown" (UNESCO Institute for Statistics, 2021).
- Labour force – The number of individuals in the age group of 15–64, who are currently employed as well as those who are unemployed and seeking employment.
- Gross capital formation – This consists of fixed assets of the economy, which includes aggregate changes in inventory levels. These fixed assets also include land improvements, plant, machinery, equipment purchases and the construction of roads, railways.

The ICT development factor employed in this study was made up of an index of telecommunication that comprised of mobile lines, fixed lines and internet penetration in order to represent infrastructure development. The Principal Component Analysis (PAC) was used to derive the telecommunication indicator through the following equation (David, 2019):

$$CIT = \alpha_1 mob\_line + \alpha_2 fixed\_line + \alpha_{3i} nternet\_access$$

Where the constants * α1, α2 and α3* represent the weights of the mobile, fixed and penetration.

Table 4.1: Definition of variables

Variable Names	**Description**	**Data Source**
EMPL	Employment, total (% of total labour force)	
LF	Population ages 15–64 (% of total population)	
ICT	composite ICT index of mobile, fixed, and internet penetration (derived using PCA)	
CAP	Gross capital formation (% of GDP)	
EDUL	School enrolment, secondary (% gross)	
GDP	Real gross domestic product as a proxy of economic growth	

4.4 Chapter summary

The aim of Chapter 4 was to highlight the methodology conducted in an attempt to achieve the empirical objectives and the reasons behind the selection of these approaches. The data sources were elaborated on and the variables were defined. The econometric models used in the study were also described. In order to obtain reliable results and reduce residuals, the chosen data were changed into natural logarithms and stationarity tests conducted before continuing with other models of integration and causality.

CHAPTER 5

EMPIRICAL RESULTS AND DISCUSSION

5.1 Introduction

The purpose of this chapter is to empirically examine the impact of ICT developments on employment in South Africa. A review on literature in Chapter 3 highlighted a possible impact of ICT developments on employment, however, no clear direction of the contribution of the effects of ICT developments on employment was observed. This therefore renders it important to evaluate the direction of causality and examine if there exists a short- or long-run relationship between the variables under study. Looking at the trends in ICT developments and labour force outcomes in South Africa, it was evident that there has been a positive trend with regard to the adoption of ICT components while the labour force outcomes showed a decline in employment. Therefore, this chapter made use of econometric models to empirically determine if ICT developments do in fact impact the levels of employment and provide results obtained from the models.

The analysis commenced by analysing descriptive statistics to assess the collected data. The study then continued to test for cointegration between the variables employing the Johansen cointegration test and the VECM to determine the long-run relationship between these factors. However, before an examination of the long-run relationship could be undertaken, these cointegration models require that stationarity tests on the data be conducted, and this study therefore tested for unit roots and the order of integration using the ADF and PP unit root tests. Finally, diagnostic tests were run to establish the stability of the results and therefore ensuring their reliability.

5.2 Descriptive statistics

Illustrated in Table 5.1 are descriptive statistics of the effects of ICT developments on employment in South Africa. The table summarises the average, maximum and minimum values of the variables, the skewness, and kurtosis and Jarque-Bera test showing the distribution of the data.

Table 5.1a: Summary statistics

Statistics	Real Gross Domestic Product	Secondary education, general people	Employment to population ratio 15+	ICT Components	GDP per capita (constant LCU)	Gross Capital Formation (% of GDP)	Population aged 15-64 (% of total population)
	ECONOMIC_GROWTH	EDUCATION_LEVEL	EMPLOYMENT_LEVEL	ICT	INCOME	INVESTMENT_LEVEL	LABOUR_FORCE
Mean	9.885913	89.56772	71.95871	87.60801	966.7909	18.48518	62.67765
Median	10.44480	87.39671	70.88000	73.75884	961.6443	18.46660	64.50690
Maximum	13.56340	109.4441	77.59000	230.1035	1897.582	23.15017	65.69501
Minimum	1.000000	68.88434	66.71000	1.000000	373.8871	12.42640	55.91291
Std. Dev.	2.576036	10.50971	2.661329	83.20366	406.6463	2.115450	3.443348
Skewness	-1.334115	0.190913	0.339559	0.451315	0.420491	-0.465623	-0.736453
Kurtosis	5.750267	2.354157	2.321026	1.652791	2.570844	3.862531	1.999638
Jarque-Bera	18.96609	0.727084	1.191183	3.396713	1.151424	2.081104	4.094808
Probability	0.000076	0.695209	0.551236	0.182984	0.562304	0.353260	0.129070
Sum	306.4633	2776.599	2230.720	2715.848	29970.52	573.0405	1943.007
Sum Sq. Dev.	199.0788	3313.620	212.4801	207685.5	4960838	134.2539	355.6994
Observations	31	31	31	31	31	31	31

Source: author’s compilation, 2021

Economic growth (GDP at constant 2010 US$) — the mean, over the period between 1990 to 2020, was calculated at USD323 billion while the minimum and maximum fluctuated between USD216 billion and USD430 billion, respectively. The distribution of economic growth is negatively skewed and economic growth is not normally distributed, as is indicative by the rejection of the null hypothesis of normality from the Jarque-Bera test statistic at both the 5% and 1% significance level.

Education level (Literacy rate of adult: total % of people ages 15+) — the mean level of education has been at 89.57% while the minimum and maximum reached 68.88% and 109.44%, respectively. The distribution in level of education is positively skewed and residuals of level of education are normally distributed as is indicative by the acceptance of the null hypothesis of normality of the Jarque-Bera test statistic (p-value > 5% level of significance).

Employment level (employment to population ratio of people ages 15+) — the mean employment level was recorded at 71.96% and the minimum and maximum at 66.71% and 77.59%, respectively. The distribution of employment is positively skewed and the residuals of employment level are normally distributed as indicative by the acceptance of the null hypothesis of normality of the Jarque-Bera test statistic.

ICT (mean annual ICT index comprising of internet usage, Mobile and Landline) — the average was calculated to be 87.61 people per 100 people over the 30-year period while the minimum and maximum were recorded at 1.00 and 230.10, respectively. The distribution of ICT is positively skewed and ICT residuals are normally distributed as indicative by the acceptance of the null hypothesis of normality of the Jarque-Bera test statistic.

Income (GDP per capita constant LCU) — the mean income has been at USD6621.09, with minimum and maximum reaching USD5517.53 and USD7582.95, respectively. The distribution of income is negatively skewed and the residuals of income are normally distributed as indicative by the acceptance of the null hypothesis of normality of the Jarque-Bera test statistic (p-value > 5% significance level).

Investment level (Gross fixed capital formation (%GDP)) – the annual mean investment level was USD18.49 billion, while the minimum and maximum reaching USD 12.43 billion and USD23.15 billion, respectively. The distribution of investment level is negatively skewed and the residuals of investment level are normally distributed as indicative by the acceptance of the null hypothesis of normality of the Jarque-Bera test statistic.

Labour force (total population aged 15–64(% of total population) — the mean for labour force was 62.68 million while the minimum and maximum are reaching 55.91 million and 65.70 million, respectively. The distribution of labour force is negatively skewed and the residuals of labour force are normally distributed as indicative by the acceptance of the null hypothesis of normality of the Jarque-Bera test statistic (p-value > 5% significance level).

Table 5.1b summarises the correlation between variables, where positive coefficients denote a positive correlation and negative coefficients denote a negative correlation. Looking specifically at the dependent variable (employment level), it can be noted that employment has a fairly strong positive correlation with all the other variables, with the exception of real GDP (-0,012790).

Table 5.1b: Correlation matrix result

	LNICT	LNCAP	LNEMPL	LNHCD	LNINCOME	LNLABF	LNRGDP
LNICT	1,000000	0,242427	0,574241	0,868521	0,901253	0,992524	-0,065289
LNCAP	0,242427	1,000000	0,672890	0,373783	0,200271	0,279081	0,553989
LNEMPL	0,574241	0,672890	1,000000	0,668710	0,504903	0,586840	-0,012790
LNHCD	0,868521	0,373783	0,668710	1,000000	0,860574	0,858851	0,004400
LNINCOME	0,901253	0,200271	0,504903	0,860574	1,000000	0,888064	-0,033730
LNLABF	0,992524	0,279081	0,586840	0,858851	0,888064	1,000000	-0,011697
LNRGDP	-0,065289	0,553989	-0,012790	0,004400	-0,033730	-0,011697	1,000000

Source: author’s compilation, 2021

5.3 Unit root and stationarity test results

Unit root test and stationarity tests results were analysed in this section in order to determine the order of integration of the variables. As discussed in Chapter 4, it is essential to conduct stationarity tests before estimating correlation between variables in order to avoid spurious results. This study employed the ADF and PP unit root test in order to diagnose unit roots and establish the order of integration. Both these tests are founded on the hypothesis that the variables have unit roots against the alternative hypothesis stating that the variables do not have unit roots. A summary of the unit root and stationarity results are given in Table 5.2. Indicated in the table is the order of integration at levels and at first difference with intercept, intercept and trend, and with no intercept and trend.

Table 5.2: Unit root tests

	Test with Intercept		Test with Intercept and Trend		Test with no Intercept of Trend		
Variable level	ADF Test	PP	ADF Test	PP	ADF Test	PP	Decision
Levels							
LECONOMIC_GROWTH	0.9225	0.9225	0.9738	0.9748	0.3242	0.3242	Not stationary
LEDUCATION_LEVEL	0.3711	0.1850	0.5978	0.9073	0.6290	0.9478	Not stationary
LEMPLOYMENT_LEVEL	0.6240	0.5474	0.8914	0.8161	0.7043	0.7016	Not stationary
LICT	0.0877	0.2983	0.9631	0.9950	0.7983	0.9851	Not stationary
LINCOME	0.3151	0.4310	0.0483	0.0556	0.8765	0.9847	Not stationary
LINVESTMENT_LEVEL	0.7978	0.7411	0.9756	0.9698	0.3140	0.3112	Not stationary
LLABOUR_FORCE	0.0152	0.0108	0.2019	0.9988	0.5221	1.0000	Not stationary
First Difference							
D(LECONOMIC_GROWTH)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	Stationary
D(LEDUCATION_LEVEL)	0.3164	0.0000	0.4711	0.0000	0.0339	0.0000	Stationary
D(LEMPLOYMENT_LEVEL)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	Stationary
D(LICT)	0.0914	0.0000	0.0378	0.0000	0.0857	0.0000	Stationary
D(LINCOME)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	Stationary
D(LINVESTMENT_LEVEL)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	Stationary
D(LLABOUR_FORCE)	0.9153	0.0000	0.5820	0.0000	0.2767	0.0000	Stationary

Source: author's compilation, 2021

The ADF unit root test results from Table 5.2 indicate that the variables – LECONOMIC_GROWTH, LEDUCATION_LEVEL, LEMPLOYMENT_LEVEL, LICT, and LINVESTMENT_LEVEL – have p-values greater than the 5% level of significance meaning that they are all not stationary at levels, with intercept and trend, and without intercept and trend. LINCOME has a p-value greater than 5% significance level when tested with intercepts and with no intercept and trend, while estimating a p-value less than 5% when tested with intercept and trend. Additionally, LLABOUR_FORCE has a p-value greater than 5% significance level when tested with intercepts and trend and with no intercept and trend, while estimating a p-value less than 5% when tested with intercept. These results suggested that the null hypothesis should not be rejected but rather reject the alternative hypothesis at levels implying that the variables are not stationary at levels.

The PP results from Table 5.2 also confirm that LECONOMIC_GROWTH, LEDUCATION_LEVEL, LEMPLOYMENT_LEVEL, LICT, LINCOME, and

LINVESTMENT_LEVEL are not stationary at levels in all scenarios (Intercept, Intercept and Trend, No Intercept and Trend) displaying p-values greater than 5% significance level. LLABOUR_FORCE showed a p-value greater than 5% significance level when tested with intercept and trend, and with no intercept and trend, however, revealing a p-value less than 5% when tested with intercept. These results further implied non-stationarity of the variables and therefore the null hypothesis cannot be rejected.

The results obtained at levels dictated the need to run the models at first difference and from the PP test it was determined that all variables are stationary at first difference at 1% significance level. Therefore, the null hypothesis cannot be accepted and the alternative hypothesis that all the variables contain no unit root will be accepted.

5.4 Johansen cointegration test

The results from the stationarity tests showed that all the variables are integrated at first difference I(1), therefore allowing for the use of the Johansen cointegration test, which was conducted to evaluate whether a long-run relationship exists between all logged variables. The test estimates the trace statistics and the maximum eigenvalue statistics of which according to Shrestha and Bhatta (2018), “the trace statistics tests for the null hypothesis of k cointegrating relations against the alternative hypothesis of k-1… [while] the maximum eigenvalue statistics tests for the null hypothesis of r cointegrating relations against the alternative of r+1”. In these methodologies, tests are estimated in sequence from r=0 to r=k-1 to a point where the null hypothesis cannot be rejected. Table 5.3 displays a summary of the cointegration test results at a 5% significance level from both the Trace and Max-Eigen tests.

Table 5.3: Cointegration result

	Test statistics	0.05 Critical value	Probability value
	Trace statistics		
None *	127.3403	125.6154	0.0391
At most 1	90.23734	95.75366	0.1128
At most 2	60.23089	69.81889	0.2283
At most 3	35.31885	47.85613	0.4313
At most 4	19.00347	29.79707	0.4927
At most 5	6.962436	15.49471	0.5820
At most 6	0.155029	3.841465	0.6938
	Max-Eigen Statistics		
None	37.10293	46.23142	0.3348
At most 1	30.00644	40.07757	0.4234
At most 2	24.91204	33.87687	0.3910
At most 3	16.31538	27.58434	0.6389
At most 4	12.04104	21.13162	0.5436
At most 5	6.807407	14.26460	0.5122
At most 6	0.155029	3.841465	0.6938

Source: author's compilation, 2021

The results indicate that the p-values – for the Trace statistics – under “None” cointegrations are less than the 5% significance level. Therefore, the null hypothesis was rejected, which state that there is no cointegration. The p-values of “At most 1”, “At most 2”, “At most 3” “At most 4”, “At most 5”, and “At most 6” are, however, greater than the 5% significance level and therefore the null hypothesis cannot be rejected. This means that there is at most 1 cointegrating equations indicating that there is cointegration among the variables and that employment, economic growth, labour force, ICT, investment level, income and education level have a long-run relationship.

The Max-Eigen test on the other hand shows that the p-values under “None”, “At most 1”, “At most 2”, “At most 3”, “At most 4”, “At most 5” and “At most 6” are greater than 5%

significance level and therefore the null hypothesis cannot be rejected. This means that there is no cointegration indicating that there is no cointegration among all the variables and that employment, economic growth, labour force, ICT, investment level, income and education level do not have a long-run relationship.

Based on the results above, it can be observed that there exists no agreement between the Trace and Max-Eigen statistics and therefore this study proceeded with the Trace statistic test which indicates that there is at least one cointegrating equation and therefore a long-run relationship.

5.5 Vector autoregression model

The study further made use of the VAR model in the process of analysing the impact of ICT developments on employment levels in South Africa. Upon establishing the Johansen cointegration test results, which revealed that all variables (employment, economic growth, labour force, ICT, investment level, income and education level) have a long-run relationship, the study proceeded to employ the VAR model in order to validate the results. The stationarity tests revealed that all variables are not stationary at levels but rather at first difference and this then renders it essential to estimate the VAR. Prior to estimating the VAR it becomes crucial to begin by establishing the lag order selection criteria from the VAR estimates, which were then followed by the diagnostics tests to validate the reliability of the model.

5.5.1 Lag length selection criteria

The results summarised in Table 5.4 show the lag selection process in the VAR model. The results indicate that the Likelihood Ratio (LR), Final Prediction Error (FPE), AIC, and HQC lag selection criteria suggests 5 lags while the SIC selection criteria points to 1 lag. This study, however, proceeded to use 5 lags suggested by the LR, FPE, AIC and HQC criteria since using 5 lags in the cointegration test indicate that there is one cointegrating equations, while using 1 lag suggested by SIC states that there is no cointegrating equations. According to Liew (2014), this discrepancy is due to the fact that the SIC selection criteria are restrictive in nature but more effective with larger sample sizes, while the AIC and FPE criteria prove to be more superior and better suited when estimating smaller sample sizes.

Table 5.4: VAR lag order selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1505,254	NA	1,43E-20	-25,83196	-25,66580	-25,76451
1	2472,489	1801,05900	1,90E-27	-41,66361	-40,33429*	-41,12398
2	2484,734	21,33820	3,61E-27	-41,03005	-38,53757	-40,01825
3	2508,326	38,22058	5,73E-27	-40,59182	-36,93619	-39,10785
4	2622,628	171,45370	1,94E-27	-41,71773	-36,89894	-39,76158
5	2861,046	328,8523*	7,96E-29*	-44,98355*	-39,00161	-42,55523*
6	2872,393	14,28095	1,70E-28	-44,33435	-37,18926	-41,43385
7	2892,647	23,04770	3,29E-28	-43,83873	-35,53049	-40,46606
8	2948,725	57,04524	3,66E-28	-43,96077	-34,48937	-40,11593

* Indicates lag order selected by the criterion.

Source: Author’s compilation (2021)

5.6. Long-run relationship between the variables

From the Trace statistic test result estimated in the Johansen cointegration test, it became evident that the null hypothesis stating that there exist no cointegrating equation was rejected since the p-value is less than the 5% significance level. Therefore, the null hypothesis stating the existence of at least one cointegrating equation could not be rejected. Upon concluding the existence of a long-run relationship among variables, the cointegrating equation was established as follows:

$$LEMPL_{t-1} = -0.99891 lnCAP_{t-1} + 0.11963 lnHCD_{t-1} + 0.06267 lnICT_{t-1} - 0.213684 lnINCOME_{t-1} - 2.095584 lnLBF_{t-1} + 0.30490 lnRGDP_{t-1} + 3.177425 \qquad (5.1)$$

Table 5.5: Long-run relationship results between the variables.

Cointegrating Eq:	CointEq1	t-statistic
LNEMPL(-1)	1.000000	
LNCAP(-1)	-0.998907	-5.07033
LNHCD(-1)	0.119629	0.47688
LNICT(-1)	0.062671	0.87075
LNINCOME(-1)	-0.213684	-275797
LNLABF(-1)	-2.095584	-0.93350
LNRGDP(-1)	0.304898	3.42243
C	3.177425	

Source: Author's compilation, 2021

Table 5.5 indicates that the ICT variable in South Africa (InICT) is positive, which means that a 1% increase in ICT development results in a 0.063% increase in employment levels. From a significance point of view, the variable's t-statistic of 0.87075 is greater than 2.05 for the 5% critical value, therefore, resulting in the rejection of the null hypothesis that ICT is not a significant determinant of employment.

The labour force (InLBF) coefficient is negative indicating that a 1% increase in labour force is associated with a 2.095% decrease in employment levels. The t-statistic of -0.93350 is smaller than 2.05 for the 5% critical value, hence the null hypothesis that labour force is a significant determinant of employment cannot be rejected, concluding that labour force significantly determines the levels of employment.

Level of education (InHCD) with a positive coefficient means that a 1% change in human capital development is related to a 0.119629 rise in employment levels. The t-statistic of 0.47688 is greater than 2.05 for the 5% critical value therefore resulting in the rejection of the null hypothesis that the level of education is not a significant determinant of employment.

The coefficient for investment (InCAP) is negative, signifying that a 1% increase in gross capital formation results in a 0.998907 decrease in employment levels. The t-statistic of -5.07033 is less than 2.05 for the 5% critical value and therefore the null hypothesis that investment is not a significant determinant of employment cannot be rejected.

The income (InINCOME) coefficient showed a negative value indicating that a 1% increase in income leads to a 0.213684 decrease in employment levels. The t-statistic of -2.75787 is less than 2.05 for the 5% critical value and therefore cannot reject the null hypothesis that income does not significantly determine employment.

Real gross domestic product (InRGDP) has a positive value signifying that a 1% increase in real GDP results in a 0.304898 increase in employment levels. The t-statistic of 3.42243 is greater than 2.05 for the 5% critical value, hence, the rejection of the null hypothesis that the level of education is not a significant determinant of employment.

5.7 Short-run relationship between the variables

In order to determine the short-run relationship between the variables, the study utilised the VECM, and the results are summarised in Table 5.6.

Table 5.6: Vector error correction estimates

Error Correction:	D(L_EMPLOYMENT_LEVEL)	t-statistic
CointEq1	-0.019761	-1.08695
D(LEMPL(-1))	-0.009923	-0.07120
D(LNCAP(-1))	-0.007688	-0.22679
D(LNHCD(-1))	0.003996	0.03253
D(LNICT(-1))	-0.004829	-0.23462
D(LNINCOME(-1))	-0.002559	-0.26966
D(LNLABF(-1))	0.524049	0.22374
D(LNRGDP(-1))	0.004046	0.50103

Source: Author's compilation, 2021

$$\Delta lnEMPt = -0.019761ECT_{t-1} - 0.009923\Delta lnEMP_{t-1} - 0.007688\Delta lnCAP_{t-1} + 0.00396\Delta lnHCD_{t-1} - 0.004829\Delta lnICT_{t-1} + 0.524049\Delta lnLBF_{t-1} + 0.004046\Delta lnRGDP_{t-1} + 0.004046 \qquad (5.2)$$

Equation 5.2 indicates that the previous period's deviation from the long-run equilibrium is corrected in the current period with an adjustment speed of 0.019761%.

In South Africa, the negative investment coefficient (InCAP) indicates that a percentage increase in gross capital formation is related to a short-run 0.0076% decrease in employment levels. The t-statistic of -0.22679 is less than 2.05 for the 5% level of significance and therefore the null hypothesis stating that investment is not a significant determinant of employment in the short-run and cannot be rejected.

The coefficient for the level of education (InHCD) is positive meaning that a 1% increase in human capital development is linked to an average short-run increase of 0.0040% in employment levels. The t-statistic of 0,03253 is greater than 2.05 for the 5% significance level and therefore the null hypothesis that level of education is not a significant determinant of employment in the short-run is rejected.

The coefficient for the InICT variable in South Africa is negative depicting that a percentage increase in ICT development is associated with a 0.004829% decrease in employment levels on average in the short-run. In terms of significance, the t-statistic of - 0,23462 is less than 2.05 for the 5% critical value, hence, the null hypothesis that ICT is not a significant determinant of employment in the short-run cannot be rejected.

The coefficient for InINCOME is negative, suggesting that a percentage increase in income is on average linked to a 0.002559% decrease in employment levels in the short-run. Its t-statistic of -0.26966 is lower than 2.05 for the 5% significance level, therefore the null hypothesis stating that income is not a significant determinant of employment in the short-run cannot be rejected.

The InLBF coefficient is positive indicating that a percentage increase in labour force is linked to a short-run percentage increase of 0.524049 in employment level. From a significance point of view, a t-statistic of 0.22374 is greater than 2.05 for the 5% level of significance and therefore the null hypothesis that labour force is not a significant determinant of employment in the short-run is rejected.

The positive coefficient for InRGDP means that a percentage increase in real GDP is associated with a short-run percentage increase of 0.004046 in employment levels. Its t-statistic of 0.50103 is greater than 2.05 for the 5% level of significance, therefore the null hypothesis stating that real GDP is not a significant determinant of employment in the short-run is rejected.

5.8 Granger causality

In order to test whether one variable is suitable to predict another variable, the Granger causality test has proved to be a useful method in this regard (Granger, 1969). Summarised in Table 5.7 are the Granger causality results and from these results, it is observed that:

- The bidirectional relationship between investment and employment shows that the two variables do not Granger cause each other as both the p-values of 0.1162 and 0.9170 for investment and employment, respectively, are greater than 0.1 for the 10% level of significance. Therefore, the null hypotheses that investment does not Granger cause employment, and that employment does not Granger cause investments are accepted.

- In determining the bidirectional causality between education levels and employment levels, the education level p-value of 0.8765 is greater than 0.1 for the 10% significance level meaning that levels of education do not Granger cause employment and therefore the null hypothesis is accepted. However, employment Granger causes education levels because its p-value of 0.077 is less than 0.1 for the 10% critical value, therefore the rejection of the null hypothesis. This then signifies a unidirectional relationship where employment Granger causes education levels but not the other way around.
- The bidirectional relationship between ICT and employment shows that the two variables do not Grander cause each other as the p-values of 0.616 and 0.5561 for ICT and employment, respectively, are both greater than 0.1 for the 10% level of significance. Therefore, the null hypotheses that ICT does not Granger cause employment, and that employment does not Granger cause ICT are accepted.
- There also exists a bidirectional relationship between income and employment. However, the two variables do not Grander cause each other as the p-values of 0.8889 and 0.8277 for income and employment, respectively, are both greater than 0.1 for the 10% level of significance, meaning the null hypotheses that income does not Granger cause employment, and that employment does not Granger cause income are accepted.
- In order to determine the bidirectional causality between labour force and employment, the labour force p-value of 0.4103 is greater than 0.1 for the 10% critical value therefore leading to the acceptance of the null hypothesis that labour force does not Granger cause employment. However, the employment p-value of 0.0692 is less than 0.1 for the 10% level of significance meaning that employment Granger causes labour force and therefore rejects the null hypothesis. Therefore, this is indicative of a unidirectional relationship where employment Granger causes labour force but not the other way around.
- The bidirectional relationship between real GDP and employment shows that the two variables do not Grander cause each other as the p-values of 0.4476 and 0.9406 are both greater than 0.1 for the 10% level of significance. Therefore, the null hypotheses

that real GDP does not Granger cause employment, and that employment does not Granger cause real GDP are accepted.

Table 5.7: Granger causality results

Null hypothesis:	**F-statistics**	**Prob.**	**Decision**
LNCAP does not Granger Cause LNEMPL	2.19232	0.1162	Accept
LNEMPL does not Granger Cause LNCAP	0.08674	0.9170	Accept
LNHCD does not Granger Cause LNEMPL	0.13196	0.8765	Accept
LNEMPL does not Granger Cause LNHCD	2.62100	0.0770	Reject
LNICT does not Granger Cause LNEMPL	0.48647	0.6160	Accept
LNEMPL does not Granger Cause LNICT	0.58980	0.5561	Accept
LNINCOME does not Granger Cause LNEMPL	0.11791	0.8889	Accept
LNEMPL does not Granger Cause LNINCOME	0.18936	0.8277	Accept
LNLABF does not Granger Cause LNEMPL	0.89762	0.4103	Accept
LNEMPL does not Granger Cause LNLABF	2.73216	0.0692	Reject
LNRGDP does not Granger Cause LNEMPL	0.80944	0.4476	Accept
LNEMPL does not Granger Cause LNRGDP	0.06123	0.9406	Accept

Source: Author's compilation, 2021

5.9 Residual diagnostic tests

The residual diagnostic tests are to test the validity of the VECM results. To test for the presence of autocorrelation, the Lagrange multiplier (LM) test was utilised. In addition to the autocorrelation test, the VEC residual heteroskedasticity test was employed to test for heteroskedasticity. Furthermore, the Cholesky of covariance test was used to test for normality of the residuals. Table 5.8 summarises the diagnostic test results.

Table 5.8: Diagnostic test results

Test statistics	Null hypothesis H_0	P-value	Decision
LM Test	No serial correlation	1.0000	Do not reject null hypothesis
Orthogonalisation: Cholesky	Residuals are normally distributed	0.0000	Reject null hypothesis
VEC residual heteroskedasticity test	No heteroscedasticity	1.0000	Do not reject null hypothesis

Source: Author's compilation, 2021

The p-value from the LM test is 1 and therefore greater than the 5% significance level. This suggests that the null hypothesis stating that there is no serial correlation cannot be rejected. In terms of the Cholesky test, the p-value of 0 is less than the 5% critical value and as a result, the null hypothesis stating that the residuals are normally distributed is rejected. Furthermore, the null hypothesis that there is no heteroscedasticity is not rejected due to its p-value of 1 being greater than the 5% significant level.

5.10 Variance decomposition analysis

The variance decomposition analysis measures the movement in the shocks of the variable itself and the other variable and this was conducted using the orthogonalised Cholesky ordering approach. The results in Table 5.9 indicate the variance decomposition of employment level for 10 periods – whereby the short period is represented as 5 and the long-run by 10. The results shown under decomposition of employment levels refer to the response of employment levels to its own shocks, shocks in investment, shocks in level of education, shocks in ICT, shocks in income, shocks in labour force and shocks in real GDP. It can be observed that employment levels' response to shocks in itself causes 82.37614% fluctuation in the short-run, decreasing slightly to 45.61870% fluctuation in the long-run in South Africa. Shocks in investment causes 13.33083% and 35.92298% fluctuation to employment levels in the short and long-run, respectively, while shocks in level of education contributed 0.333159% in the short-run and 5.178682% in the long-run. In the short-run, ICT causes 0.835816% fluctuations to employment levels but increases to fluctuations of 3.972876% in the long-run. Shocks in income leads to short-run fluctuations of 0.370115% in employment levels and increasing to 1.568954% in the long-run. Labour force contributes fluctuations of 1.289209% and 1.485215 to employment levels in the short and the long-run, respectively. Lastly, real GDP contributes 1.464733% fluctuations to employment levels in the short-run and 6.252592% in the long-run.

Table 5.9: Decomposition of LNEMPL

Period	S.E	LNEMPL	LNCAP	LNHCD	LNICT	LNINCOME	LNLABF	LNRGDP
1	0.003667	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.004815	99.65098	0.012473	0.003162	0.030215	0.110986	0.189839	0.002341
3	0.005506	98.99699	0.042976	0.013936	0.078248	0.296791	0.564781	0.006281
4	0.005965	98.16148	0.091580	0.036085	0.128474	0.506034	1.065698	0.010646
5	0.007064	82.37614	13.33083	0.333159	0.835816	0.370115	1.289209	1.464733
6	0.00784	73.16084	20.58292	0.645917	1.433497	0.506251	1.450787	2.219782
7	0.008445	66.60839	25.27097	0.986280	1.959979	0.876437	1.559182	2.738757
8	0.008937	61.56856	28.48272	1.348442	2.413242	1.402151	1.622847	3.162035
9	0.009786	52.69327	32.73031	3.808783	3.223835	1.298613	1.567285	4.677901
10	0.010595	45.61870	35.92298	5.178682	3.972876	1.568954	1.485215	6.252592

5.11 Impulse response analysis

After having analysed the shocks and fluctuations on employment and ICT, an impulse response analysis had to be conducted in order to determine the time path response of the VAR system to different shocks. David (2019) alludes to the point that in order to identify the reaction of endogenous variables to shocks, an impulse response analysis needs to be conducted. This is because the impulse response analysis measures the unit shock applied on each series and its impact on the VAR system. The study, however, focussed only on ICT and employment levels as depicted in Figure 5.1.

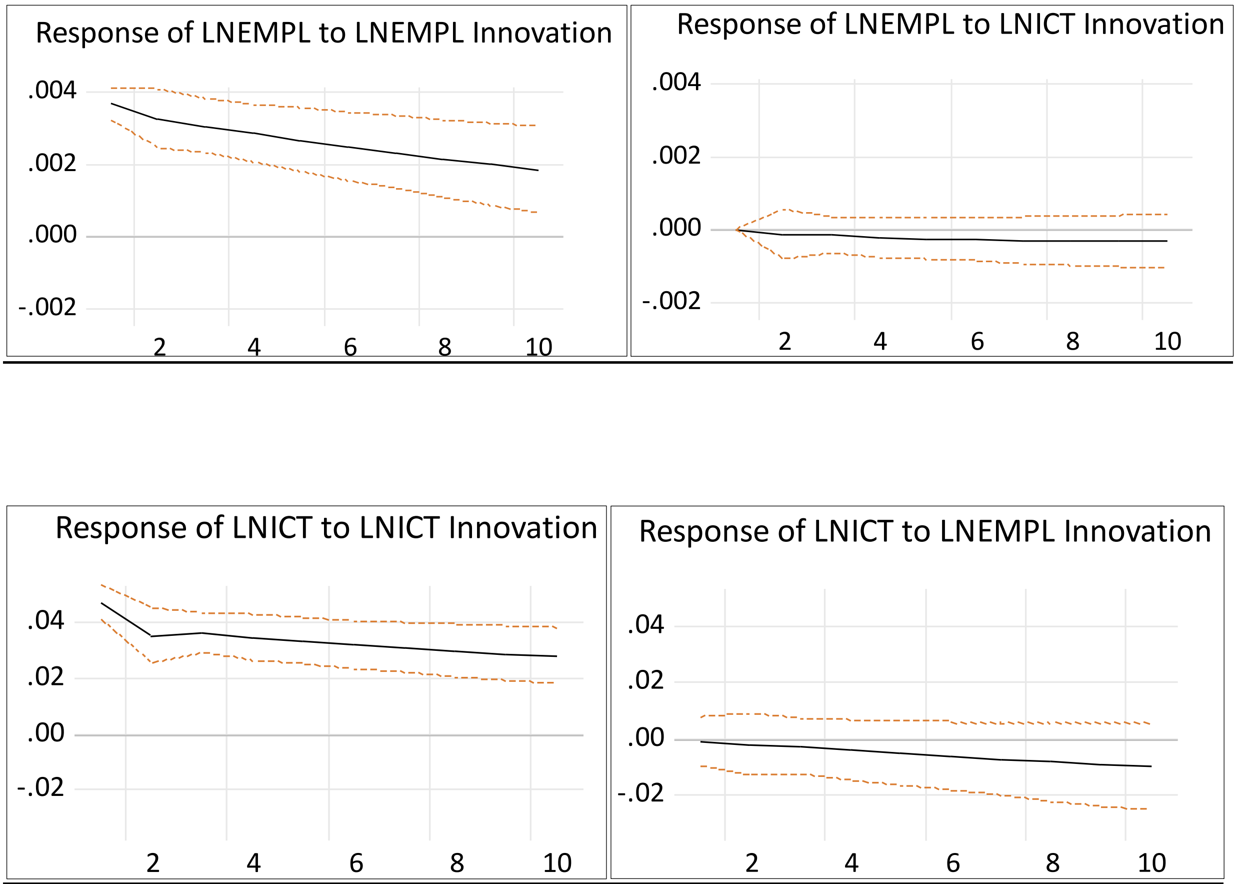


Figure 5.2: Employment level and ICT response to Cholesky one standard deviation innovations

It is evident in Figure 5.1 that levels of employment respond positively to own one standard deviation shock, however, showing a steady decline over the long-run. Employment levels show a negative reaction to a one standard deviation shock to ICT throughout the 10 periods displaying a further downward trend in the long-run. A one standard deviation shock of ICT to itself displays a positive reaction with a gentle decline over the 10 periods while showing a negative reaction, which further declines in the long-run, to a standard deviation shock on employment levels. These results indicate that fluctuations in employment have positive yet declining effect on itself in the long-run while fluctuations in ICT resulted in a negative reaction on employment levels.

5.12 Discussion of the results

The results obtained from these findings indicate that the data on variables are normally distributed in accordance with the Jaque-Bera test statistic. The unit root tests (ADF and PP) proved to be stationary at first difference, which implied the ability to continue towards testing for cointegration. After conducting the Johansen cointegration test, it is observed that the Trace statistics estimates are not in agreement with the Max-Eigen results and therefore the study followed through with the Trace statistics results, which estimated at most one cointegrating equation and therefore the existence of a long-run relationship. Subsequently, the VAR model determines that all variables are significant determinants of employment in the long-run where ICT, real GDP, and human capital development indicate a direct relationship with employment. In other words, an increase in either of these variables will result in an increase in employment levels. Looking specifically at the impact of ICT developments on employment in the short-run, there appears to be no substantial impact on employment. The results also indicate that increasing investment, income, and levels of the labour force have a negative impact on employment in the long-run. It is understood from theory that the larger the labour force than the market can absorb, the more competition among labourers, and the lower wages become in accordance to the principle of supply and demand. The VECM results portray ICT developments as an insignificant determinant of employment in the short-run. Furthermore, the Granger causality test reveals a bidirectional relationship where ICT does not Granger cause employment and vice versa. Econometric models indicated that ICT is a significant determinant of employment levels and has a direct relationship with employment in the long-run, however not so impactful in the short-run. This may be attributed to the need for human capital development so that the labour force skills may be aligned to the current work requirements, as evidence gathered from theory has indicated, which generally takes longer as policies need to be developed, trailed and implemented before the realisation of results. From a causality standpoint, the results showed that there is no causal relationship between ICT and levels of employment. Therefore, the current trend of decreasing levels of employment and rising ICT activities in South Africa should not necessarily be concluded as a major contributor to the cause-and-effect relationship but rather other factors such as capital investment and economic growth need to also be thoroughly interrogated

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

History has shown how industrial transformations in societies have been brought forward by technological advances as a result of advanced knowledge affecting the ways of work (Wessels, 2020:1). With every industrial revolution, literature explains that it became evident that the introduction of innovative technologies influenced the workforce in terms of employment levels and the requirement of new skills to complement the complexities that arise. The ICT sector has shown to be a crucial factor in economic growth in numerous developed and developing countries and through this awareness, many institutions have over the past years invested in R&D strategies that will allow for a smoother transition into and the adaptation of technological advancements brought about by the 4IR. However, many argue that the effects of ICT developments may have a negative impact on the labour market resulting in increased levels of technological unemployment as technology replaces human resources. South Africa is faced with the three main challenges of unemployment, poverty and inequality. Policymakers have adopted the NDP as a framework towards creating inclusive economic growth forecasted at mitigating those challenges. The country has seen annual increases in unemployment in line with the stagnant economic growth that has led to minimum growth opportunities. The government has, however, been putting measures to stimulate growth capable of absorbing the large pool of unemployed labour.

This study therefore investigated the impact of ICT developments on employment in South Africa by analysing empirical data from 1990 to 2020. The primary objective of the study was to examine the relationship between ICT developments and employment in South Africa and to determine whether ICT developments are a major determinant of employment levels in the country. With these main objectives, the study employed econometric methodologies and tools to determine the short-run and long-run relationship between the variables. This chapter summarises the study and indicates how objectives were achieved and finally offer recommendations in line with the findings highlighted in the previous chapter.

6.2 Summary of the chapters

Chapter 1 was responsible for initially introducing capturing the background of the study and then highlighting the problem that the study aimed to address by posing a research question that would then guide the study. Presented in the introduction, was the concept of ICT and employment in South Africa. A brief history on technological advancements was given in relation to industrial revolutions and the effects they have had on the labour market. Clear theoretical and empirical objectives were formulated in alignment with the primary objective. Penultimately, the chapter motivates the significance of undertaking the study and the contribution to the wider body of knowledge. The chapter closes by giving a brief overview on the chapters to follow.

Chapter 2 explored and gave an overview on the labour market outcomes and ICT developments in South Africa. The chapter begins by examining the concepts, definitions, and trends in the labour market dynamics. It also explains how the labour market dynamics are a result of complex interaction happening within and between economic institutions where human resources are endlessly reallocated across organisations, industries and geographic locations (Guerrero & Axtell, 2013). The study then looked at a broader view on employment trends and thereafter narrows it to the South African context by looking at statistics. The second part of the chapter gives an overview on ICT developments and their importance in maintaining a country's economic growth. The South African ICT market was then examined looking at data from 2015 to 2020 focussing specifically on telecommunications (which included ICT revenues, infrastructure investments, and internet penetration).

Chapter 3 explored literature to understand the theoretical and empirical knowledge on ICT and employment. Initially, the concepts, characteristics and evolution of ICT developments are examined alongside the role that these technological transformations have and continue to influence societies. The study took a detailed look at the industrial revolutions leading up to the current era, the 4IR and examines the trends in terms of the main goals, main technical achievements, main industries, relevant skills on the labour market, and the rate of change among other factors. The complexity and interconnectedness of the current technological era were highlighted as evidently having an inevitable impact on industries, societies and the future of work. Employment, as the dependant variable in this study is subsequently examined looking at its definitions and relationship to a country's economic status. The literature review also pointed out how employment levels are affected by challenges of declining economic growth that results in a lack of sustained job creation. Furthermore, some theories of employment, i.e., classical theory, Keynes' theory, and Okun's law, were considered in the theoretical part of the study. From an empirical review, a number of previous studies were examined in order to observe the practical impact on ICT on employment and from these studies, there is no consensus on the direction of causality between the two variable and the impact on ICT on employment therefore still remain theoretically speculative and empirically uncertain.

In Chapter 4, the study gave a detailed explanation on how the objectives were to be achieved by performing specific econometric tests in an attempt to analyse the relationship between ICT developments and employment levels. This chapter provided a clear and comprehensive view of the methodological approach employed in the study, a clear description of the variables used, collection of data and the econometric model that were utilised. These models included the unit root tests (ADF and PP test), Johansen cointegration test, the Granger causality test, the ECM, and the VAR model. For example, the Granger causality test was used to test the causal relationship between ICT developments and employment, while the estimation of the short- and the long-run relationship between the different variable were conducted using the ECM. In addition, model selection criteria were provided showing how the study achieved the models it employed. Finally, the sources of data to be analysed, which spans from 1990 to 2020, were listed and the chosen variables were defined.

The objectives of the study were achieved and the findings presented in Chapter 5. In order to determine the impact of ICT developments on employment, econometric models were used by beginning with descriptive statistics and testing for stationarity. The descriptive statistics revealed that the data for the all variables in the model (except economic growth) was normally distributed as implied by the acceptance of the null hypothesis of normality from the Jaque-Bera test statistic where the p-values of the variables were greater than the 5% level of significance. The test for stationarity was conducted using the ADF and PP unit root tests and all variable were not stationary at levels I(0), however, after running the model at first difference I(1), all variable were stationary at the 1% level of significance meaning that all variables contained no unit root. Since all variables were integrated at first difference, the analysis could then proceed to test for cointegration to determine the existence of a long-run relationship between the variables by employing the Johansen cointegration test. The results from the Trace statistics estimated that there is at least one cointegrating equation and therefore a long-run relationship between the variables, while the Max-Eigen statistics estimated no cointegration among the variables. The study, however, proceeded with the Trace statistics results of at least one cointegrating equation and validated the long-run relationship using the VAR model. The model indicated that all variables are significant determinant of employment in the long-run. ICT, real GDP, and human capital development indicated a direct relationship with employment in the long-run, in other words, when these variables increase, so do levels of employment. However, gross capital formation, income and labour force levels displayed an inverse relationship with employment in the long-run. The short-run relationship was also examined through the VECM and the result indicated that gross capital formation, ICT and income are not significant determinants of employment in the short-run. Real GDP, human capital development and labour force are, however, significant determinants of employment in the short-run. Moreover, residual diagnostic tests were conducted to validate the VECM results and it was determined that the model had no serial correlation and heteroscedasticity.

In addition, the Granger causality test was conducted and it was established that a bidirectional relationship exists between investment and employment; ICT and employment; income and employment; and economic growth and employment. These variables, however, do not Granger cause each other. In contrast, a unidirectional relationship exists between levels of education and employment, and between labour force and employment, where employment levels Granger causes both education and labour force.

6.4 Limitations of the study and further research areas

One major limitation experienced in this investigation is the lack of empirical literature within South Africa. Most studies were based on theoretical analysis of the relationship between the two main variables, ICT developments and employment, and less on statistical data and empirical analysis. Another limitation was not being able to utilise other variables such as research and development expenditures to supplement the ICT development component. It is therefore recommended that further studies focus on a wider range of variables that could be useful in covering technological innovations as a whole.

6.3 Chapter summary

The study was guided by the primary objective of investigating the relationship between ICT and employment in the context of South Africa and in order to achieve this objective, it was separated into theoretical and empirical objectives. The theoretical objectives were met in Chapters 2 and 3 while the empirical objectives were achieved in Chapter 5.

Theoretically, literature revealed how technological transformations during industrial revolutions were a key driver influencing the labour market in terms of employment levels and skills requirements. It became evident that during the first two industrial revolutions, the lower skilled population of the labour force was easily absorbed into the labour market due to the labour-intensive nature of industries. ICT developments were still in infancy and could only allow for expansion of industries leading to mass production therefore requiring more human capital with minimal skills. As the Third Industrial Revolution took centre stage, ICT developments were capable of computerising operations and therefore requiring a much more skilled labour force. This then resulted in shift in favour towards the higher skilled employees and less on the lower skilled. With these developments, it is expected that unemployment among the lower skilled would increase due to technological substitution, however, literature indicates that as new ICT developments are introduced, new industries are created, which are then able to re-absorb the displaced workforce and maintain equilibrium. ICT developments could therefore be considered as having a positive impact on employment in the long-run as determined in literature. In South Africa this has not been the trend as statistics reveal an increase in ICT developments and a decrease in employment levels over the past decade. However, this deviation from theory should not immediately attribute the decrease in employment levels to ICT developments as there could be other factors involved such as the sluggish economic growth. Therefore, a need for empirical analysis was crucial to determine causality and the extent of the relationship between the two variables.

Empirically, the results from the econometric models indicated that ICT is a significant determinant of employment levels and has a direct relationship with employment in the long-run, however not so impactful in the short-run. This may be attributed to the need for human capital development so that the labour force skills may be aligned to the current work requirements, as evidence gathered from theory has indicated, which generally takes longer as policies need to be developed, trailed and implemented before the realisation of results. From a causality standpoint, the results showed that there is no causal relationship between ICT and levels of employment. Therefore, the current trend of decreasing levels of employment and rising ICT activities in South Africa should not necessarily be concluded as a major contributor to the cause-and-effect relationship but rather other factors such as capital investment and economic growth need to also be thoroughly interrogated.

6.4 Recommendations

Theory alluded to the need for an economy to align its current and future skills with the current and future workplace requirements in order to maintain employment stability. It was theoretically and empirically observed that ICT developments have a positive long-run impact on employment, however, this opportunity can only be leveraged through the upskilling and reskilling of the current labour force as they are required to develop the skills needed to handle the disruptive effects of ICT developments in the workplace. A large segment of South Africa’s labour force comprises low to semi-skilled employees with limited digital capabilities, which makes it a challenge to absorb this portion into a labour market that is ICT-driven and requires a certain level of technological knowledge. Government policy on education, training and development, as proposed in the NDP needs to be revised with more emphasis placed on the knowledge economy and its digital dimensions. This means focus should not only be placed on transforming the learning system towards the fields of science, technology, engineering, and mathematics (STEM), but rather incorporate adaptable skills such as interdisciplinary knowledge. Analytical and critical thinking skills, creativity and complex problem-solving to meet the needs of this rapidly changing working environment.

The South African Presidential Commission has, however, proposed recommendations that are aimed at preparing the country for these drastic societal and workplace transformations. These include investing in human capital development, creating an AI institute, securing and availing data to enable innovation, and building 4IR infrastructure. Implementation of these recommendations have not yet manifested as a result of economic and political instabilities and it should therefore be these issues that needs to be urgently addressed. With the velocity of these ICT implementations by industries, the country faces a risk of lagging behind in preparing its workforce and therefore implementation efforts should be policymakers' priority. In addition, due to the quality and accessibility of education and training in the country, organisations should take it upon themselves to facilitate a learning culture in order to prepare their employees for the future work requirements. The accelerated uptake of digital domains brought about by the Covid-19 pandemic has created numerous platforms that are capable of delivering education and skills further and wider than before, and it is therefore this opportunity that should be leveraged on to minimise the skills deficit.

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