UNIVERSITY OF KWAZULU-NATAL ™

Digital transformation and its effects on socioeconomic outcomes in South Africa: A micro-analysis of digital transformation on economic and social welfare

By

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Abstract

Digital Transformation is the present era's wave of technological transformation, pervasive and fast-paced with the promise of unparalleled human development and progression. Various studies have presented opportunities in sustainability, increased income, increased opportunities for entrepreneurship, social inclusion and equalization. However, challenges have also been noted including technology-induced job displacement and its potential to displace the incomes of people.

This study is an attempt to map the societal conditions under which digital transformation can be instrumental in generating net social and economic welfare. Using a mixed-methods approach, the study investigates socioeconomic dynamics of individuals and households, termed the physical divide, juxtaposed against the digital transformation processes.

In one of the major findings of the study, it was concluded that where digital transformation occurs under broadly under-skilled labour force, and poorly resourced social institutions and arrangements, digital transformation will more likely exacerbate socioeconomic inequalities leading to net welfare loss. The study also established the existence of a physical and digital divide of long duration in South Africa, with the inequalities likely to engender losses in welfare due to fast-paced change under digital transformation. The study also established that socioeconomic characteristics, skills and job competencies differ sharply across population groupings and continue based on access to developmental opportunities, assets, facilities and services which must be resolved for successful digital transformation.

Declaration

I, Tawonga Rushambwa, declare that

1. The research work undertaken in this report, except where otherwise indicated represents my original work, thinking and ideas.
2. The thesis has not been submitted for any degree or examination at any other academic institution or university.
3. This thesis does not contain other persons' data, pictures, graphs or other information unless specifically acknowledged as being sourced from other persons and/or institutions.
4. The report does not contain other persons' written work unless specifically acknowledged as being sourced and properly referenced as authorized according to research practice. Where external written work or research sources have been quoted,
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5. The graphics, pictures, tables and any other illustrations used in this research study were constructed by the researcher. No part has been copied and imported into the study from online sources unless specifically acknowledged, with the sources being detailed in this research report.

Signed: *Rushambwat.*

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To Dr Danford Tafadzwa Chibvongodze

To Rene D Mcfadden,

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List of Acronyms

AI	Artificial Intelligence
BBBEE	Broad Based Black Economic Empowerment
CT	Critical Theory
3D	Three Dimension Printing
DT	Digital Transformation
EGM	Endogenous Growth Model
ICT	Information and Communication Technology
IT	Information Technology
KMO	Kaiser-Meyer-Olkin measure of sampling adequacy
NIDS	National Income Dynamics Study
OECD	Organisation for Economic Cooperation and Development
PCA	Principal Components Analysis
SALDRU	Southern Africa Labour and Development Research Unit
SEIFSA	Steel and Engineering Industries Federation of Southern Africa
SME	Small Medium and Emerging Businesses
STATS SA	Statistics South Africa
WEF	World Economic Forum

CHAPTER 1: INTRODUCTION AND RESEARCH CONTEXT

1.1. Research background

Digital transformation (DT) is broadly defined as the technological transformation of society through innovative digital technology infrastructure that fundamentally increases the intensity of technology use in social and economic life (Khan, Khan and Aftab, 2015). DT has been seen as the equivalent of this era's technological revolution, ushering in new arrangements and organisation of economic activity, social interaction and governance. Economic history argues that periods of technological transformation in the past have been associated with uncertainties that necessitated social and economic policy responses to influence and shape positive and negative outcomes of their transformative effects. Examples of such policies are the policies on juvenile labour, working hours and conditions, public policy and corporate social responsibility in the first and second industrial revolutions (Mühleisen, 2018).

The previous periods of technological transformation were also associated with clear lags between technological development and its gradual adoption into the societies, and these lags allowed the design of effective policies, upskilling and some level of mapping of the effects of the technologies on societies (Peruzzi, 2014). As a result, technology adoption was gradual, institutionalised and based on policy responses that shaped economic outcomes. Thus, societies were able to adapt themselves and reconstruct their skills in response to technological transformation bringing about increased gains in economic productivity, social welfare and human development as new arrangements of social organisation and accompanying policies enabled these societies to respond to the dynamics of technology-induced change.

In this research study, the focus is on digital transformation and its effects on socioeconomic outcomes in South Africa with a focus on the micro-level dynamics of individuals and households within the context of broader digital technology-induced socioeconomic transformation. In the economics and business research literature, studies have investigated the effect of digital technologies on economic growth and productivity (Pollitzer, 2018), inclusive digital transformation (Manda and Backhouse, 2017), the nature of employment and job creation under digital transformation and associated challenges (De Ruyter, Brown and Burgess, 2018; Aly, 2020). Others have focused on the management of digital transformation for business efficiency (Ndemo and Weiss, 2017; Anthony Jnr, 2020). Most of these studies have focused on the evolution of digital transformation within the context of very advanced economies in Western Europe and North America while advancing strategies for African economies based on models of these economies. This study while borrowing concepts from this line of scholarship advances the idea that successful adaptation to digital transformation requires an understanding of its evolution based on a contextual understanding of the dynamics of individuals and institutions in the African economies experiencing digital transformation. In a study of ICT projects for human development, this discrepancy between contextual community needs and dynamics and goals of the ICT projects were found to be the key explanation for unsustainable technological approaches and divergence between information systems deployed and local realities (Pollitzer, 2018). The study focusing on inclusive digital transformation concluded of a broader role of government, industry, higher education and civil society in fostering cohesion addressing social, economic and other challenges inhibiting successful inclusive digital transformation. However, the contextual dynamics of the individuals being targeted through such recommended institutional coalitions for planned transformation were not considered (Manda and Backhouse, 2017). Another study, on Africa's emerging digital transformation argued for challenges of digital transformation caused by the marginal nature of digital transformation in Africa at large with the issues being relegated to only business and economy-related issues while not focusing on the dynamics of the individuals within the societies (Ndemo and Weiss, 2017). This study argues for a need for contextual analysis of socioeconomic issues of individuals in understanding the effects of digital transformation and how policies can be shaped to create and maintain society's socio-economic welfare.

Historically, changes brought by technological transformation have resulted in changes in work organisation and consequently skills required for many forms of employment. Typically, low to middle-skilled jobs have been a risk, and some forms of work and industries have disappeared, with such displacement addressed through retraining, creation of new industries and new forms of work (Aly, 2020). However, the historical survey of technology development also shows that the technologies were built around the use of labour, with technology being viewed as labour augmenting. The present era diverges from this premise in that the technologies affect labour in distinctive ways, displacing labour and creating new ways of relations between labour and technology (Abolhassan, 2017). There is thus a need to have a broader understanding of the characteristics and mechanics of the contemporary digital transformation, its effects on labour, income and societies so that interventions and policies can be designed to maximize welfare in the context of dynamic change (Balsmeier and Woerter, 2019).

1.2. The research problem and purpose of the study.

Adaptation to technological transformation has always been determined by the ability of the societies to develop the skills and institutions that meet the demands of the changing economic and social environment, brought about by technological change (Fischer, Startz and Rudiger Dornbusch, 2011; Burchardt and Maisch, 2019). The capacity of individuals to develop skills and equip themselves is influenced by their socioeconomic conditions, such that socioeconomic analysis yields vital insights into the ways individuals and households respond to change. It is this link between socioeconomic conditions and human capital endowments that will determine how DT will influence the welfare of individuals and households. The socio-economic analysis thus yields important insights into the structural foundations for assessing the effects of DT on individual and household socioeconomic welfare.

Despite the surge in interest in business, political and academic circles in the seeming inevitability of DT to alter where people will live; their working arrangements; and how they will interact amongst themselves, and with organisations; there is a lack of understanding on how digital technologies will impact businesses, societies and the welfare of individuals (Langley *et al.*, 2021). Although studies in business and information technology have dealt with the subject of smart technologies from their specific point of view, there appears to be a lack of comprehensive approaches that explain DT and its consequences on socioeconomic outcomes using a microlens analysis (Fredette *et al.*, 2012; Langley *et al.*, 2021).

According to some studies, DT can improve the prospects of marginalised societies and geographies (Milbourne, 2010; Zhou and Liu, 2019; ElMassah and Mohieldin, 2020). Although the argument is that DT eliminates the spatial divide through communication technology and the internet of things (Manda and Backhouse, 2017; ElMassah and Mohieldin, 2020), there has been little analysis of conditions that enable these gains through increased connectivity. This study takes into consideration the spatial dynamics of individuals and socioeconomic characteristics to provide a clearer assessment of how DT can be a force of spatial poverty reduction, thus contributing to this important area of research.

Another study that has examined DT and adaptation in South Africa, has undertaken a macro-level analysis, with inferences based on secondary data without micro-analysis of the socioeconomic conditions of South Africa (Manda and Ben Dhaou, 2019). The study postulated that increasing inequalities in most developing countries South Africa included raises concern of the imminent fourth industrial revolution where digital access and inclusion have become critical. Furthermore, South Africa is argued to remain the leading unequal society in the world, with DT likely to increase these inequalities with economic and other opportunities brought about by the fourth industrial revolution most likely going to benefit those with access (Manda and Backhouse, 2017; Manda and Ben Dhaou, 2019). As a result, there have been arguments that the role of government should be to intervene and address these inequalities before they worsen (Calvo and Dercon, 2009; Shepherd and Brunt, 2013). In this study, the argument is proposed that these inequalities are diverse and will require differentiated interventions such that educational needs, digital access and other challenges cannot be treated from a macro-perspective. A micro-level analysis of the national income dynamics study is undertaken to analyse and report the socioeconomic patterns among individuals so that interventions and policy instruments can be designed to help meet the challenge of digital transformation.

It has been argued that while the future is unknown concerning the outcomes of digital transformation, central issues in analysing the effect of new and emerging technologies on jobs in the future will require an understanding of the linkages between new technologies and innovations and identify the forces and mechanisms that destroy jobs, those creating jobs and their interactions (Nübler, 2016). This study addresses this need by providing an in-depth socio-economic analysis combined with an analysis of digital transformation, its characteristics, processes and outcomes so that opportunities can be placed within the context of the individuals and their adaptation capacity. This further fills the need alluded to in another paper of the need for future research to investigate how government, industry, higher education and civil society collaborative partnerships can foster social cohesion in addressing social, economic, governance and other challenges threatening successful inclusive DT (Manda and Ben Dhaou, 2019).

1.3. Theoretical foundations of the study

The aforementioned issues of digital technologies, technological transformation, skills and socioeconomic issues led the candidate to search for theories relevant to economic growth and human development. The thinking around economic growth theory required a theoretical lens bringing together technological transformation, productivity, human capital and institutions and assumes the deliberate role of agents in shaping technical advance, with the choice leading to the theory of endogenous growth as the framework for this study (Romer, 1994; Fedderke, 2002; Jones, 2019).

Endogenous growth theory emerged in the 1980s as an alternative to the neoclassical growth theory and sought to find explanations around differences in income among countries, particularly the divide between developed and developing countries. According to the proponent of the model, Romer (1980), technological advance/change is a deliberate outcome of the actions of economic agents undertaking investments in research and development and innovation leading to technological advance. The model proposed that sustainable productivity growth is influenced by deliberate internal processes particularly human capital development, innovation and investment capital (Romer, 1994). The core argument of endogenous growth theory is that productivity improvements are tied directly to faster innovation and expanding investments in human capital, as such these economists proposed an interventionist role of government and private sector institutions in nurturing innovation initiatives and through the use of directed incentives for individuals and firms to be more creative and entrepreneurial such as research and development and intellectual property rights (Romer, 1989; Jones, 2019).

The model is expressed as follows:

$$\Delta Y_t = [(1 - a_k)\Delta K_t)^{\propto}[\Delta A_t(1 - a_L)\Delta L)_t]^{1-\propto}$$

(Jones, 1995, 2019)

According to this model, changes in income result from contributions of the capital, physical and human and productivity explained by the technological apparatus of the economy, with the technology accounting for the largest share of income (Romer, 2011). The postulation above also shows that technology initially was assumed to augment human productivity, hence the initial policy prescriptions around interventions directed at developing high-end human skills such as creativity, innovation, analytical skills, critical thinking and entrepreneurship. Socioeconomic welfare is therefore determined by the role of human capital, technology and its ownership, with individuals whose skills are aligned with the developing technological model experiencing welfare advancement and those who are marginally connected experiencing welfare losses. While spillover effects mean that technology can power industries and sectors that are non-technology based, these will depend on human capital, since technology-based displacement will reward high-end human skills expressed in creativity, innovation, design thinking and collaborative skills, which aspects of the model are microeconomic (Spear and Young, 2016).

1.4. Research aims, objectives and questions

The primary objective of this research study is to provide a micro-level explanation of the effects of the shape and processes of DT on socioeconomic outcomes for South Africa based on the thinking informed by the endogenous growth model. The study argues that the outcomes of DT are determined by the socioeconomic conditions or the physical divide of the society experiencing digital transformation. The expected outcomes of this research are: (1) to provide a microlevel socioeconomic profile of individuals and households in South Africa, (2) to explain digital transformation, its conception, processes/characteristics, opportunities and challenges and (3) explain how DT will affect individuals and households based on explained socioeconomic profile.

1.4.1. Research objectives

In meeting the above-stated specific outcomes, the following objectives were pursued:

1. To investigate how socioeconomic conditions of individuals and households shape the ability to develop human capital and other competencies.
2. To assess the effect of digital transformation on socioeconomic outcomes of individuals and households across diverse observed socioeconomic characteristics and conditions.
3. To analyse the interaction between digital transformation and socioeconomic dynamics to enable contextualisation in the design of interventions in form of policies or action plans.
4. To describe the opportunities and challenges of digital transformation for individuals and households in South Africa.
5. To explore pathways of adaptation towards digital transformation, how opportunities can be maximized and challenges mitigated to minimize adverse socioeconomic outcomes and their destabilizing effects.

1.4.2. Research questions

Research studies are motivated by an overarching question and the main question in this research study is, "Given the observed socioeconomic conditions of individuals and households in South Africa and the processes of digital transformation, what can be done to adapt to potential changes in welfare both positive and negative". To address this question, the following sub-research questions are answered in this study.

1. Given that human capital is central to individual adaptive potential in digital transformation, how do observed socioeconomic conditions affect observed patterns of human capital development?
2. How will DT affect the welfare of individuals and households in their societies?
3. What are the observed interactions between DT and socioeconomic conditions?
4. What are the expected opportunities and challenges of DT for individuals and households in South Africa?
5. How can the expected outcomes of DT be shaped so that welfare gains can be maximized and welfare losses minimized?

1.5. Significance of the research study

The thesis uses as its departure the premise that other researchers have published important research on the impacts of DT on societies. However, the study argues that the treatment of the subject concerning socioeconomic issues had been inadequate with most findings based on inferences and conjectures based on data not contextual to the conditions of South Africa (Blignaut, 2009; Manda and Backhouse, 2017; Ndemo and Weiss, 2017).

The significance of this research study rests on the assumption that it will assess DT based on the socioeconomic context of individuals and households as the true basis of determining inclusive digital transformation, social cohesion and welfare. The thesis undertakes a varied and comprehensive analysis of the physical and digital divide among South Africans, tracing marginal changes over a longer time horizon. This is compared to the processes of DT thus creating a realistic basis for assessment of the impact of digital transformation on society. The study thus is of relevance to South Africa's welfare, while building the framework for discussions and debates in an important area of academic and policy research as digital change will constitute policy and political economy for the coming decades (Misuraca, Pasi and Viscusi, 2018; Manda and Ben Dhaou, 2019).

1.6. Research strategy

This study adopts a quantitative nested explanatory sequential mixed methods approach employing quantitative and qualitative methods in data analysis to arrive at the findings and conclusions of the research. Quantitative nested implies the study is built on quantitative premises, in this case, analysis of quantitative data and its results as the basis from which qualitative methods and results can be considered. The sequential approach directs priority of methodology with quantitative methods forming the framework of inquiry and qualitative methods coming last and providing explanations to the findings of the quantitative inquiry (Creswell and Creswell, 2017). Finally, the methodology is explanatory through qualitative results explaining the outcomes of patterns observed in quantitative analysis concerning digital transformation on socioeconomic outcomes.

Quantitative methods are implemented through descriptive and inferential analysis of the National Income Dynamics Study data that focuses on socio-economic dynamics of individuals and households in South Africa and is nationally representative (Brophy *et al.*, 2018). In preparation of the quantitative data for analysis, dimension reduction through principal components analysis (PCA) was used to reduce multiple variables measuring similar aspects into composite variables. The outcome of PCA were composite variables employed in descriptive analysis with the mean being the central parameter of the descriptive analysis, with tabulations of the marginal change in the mean tabulated across the 5 waves of the NIDS data (Chapter 5).

The second part of the analysis employed the Multiple Linear Regression (MLR) model, which uses several explanatory variables (or feature variables) to predict changes in the response or target variable (Creswell and Creswell, 2017). Using the MLR model, variables measuring socioeconomic characteristics, job competency and skills of individuals were used as explanatory variables to assess their influence on the response variable measuring the digital index. The results of the inferential analysis showed that unique socio-economic, skills and job competencies were influential on specific aspects of the digital index as well as for different population groups as presented in Chapter 5.

Qualitative research encompasses the use of qualitative data such as textual data from interviews, audio recordings, video files, podcasts, archival documents and/or observational data, with the intention of understanding non-quantifiable aspects of a phenomenon. (Creswell and Creswell, 2017). Qualitative research methods are designed to assist researchers in understanding people and the thinking that drive social and cultural contexts in which they live and interact and provide the tools and effective approaches for inquiring about complex phenomena in emerging or developing issues (Paulus and Lester, 2021). In carrying out the qualitative analysis, transcribed textual data was used sourced from focused group discussions conducted by the WEF between 2016 and 2019 concerning the emerging digital transformation.

In the analysis, a two-stage thematic analysis was used. Since there were stated research questions and a theoretical framework, a coding template was developed and used in initial thematic coding (semantic coding), which was followed by latent coding to analyse the underlying ideas which were being communicated in the interviews. Latent analysis was undertaken using the inductive coding approach as proposed by Thomas (2006) (Thomas, 2006). Thus, the outcome of the mixed methodological analysis was a consideration of the readiness of South Africa in terms of socioeconomic indicators and an understanding of digital transformation, its characteristics, effects and processes. The analysis is summarized in the table below:

Table 1.5.1: Outline of the analytical phase of this study.

Phase	Purpose	Data Source
Qualitative Analysis **Phase 1: Deductive coding** (1A)	The prepared transcripts were initially analysed with the broad categorisation of the data based on the themes on the coding template. The coding template guided the broad themes and data to extract from the transcripts of the raw data	Transcripts based on transcribed video recordings of discussion forums on DT at WEF's Davos 2016-2019 conferences.
Phase 2: Inductive latent coding (1B)	The second stage analysis was designed to extract underlying ideas and their implications and outline the deeper non-surface aspects of digital transformation. The grouped qualitative data following semantic coding (1A), was subjected to inductive analysis, with emerging themes and patterns in the data being grouped under new codes and notes written on meanings attached to the emergent themes. These themes were compared for similarities and grouped into larger themes, from which conceptual	

	definitions and substantive conclusions on digital transformation were reported (Chapter 6).	
Quantitative Analysis Phase 1: Descriptive analysis (2A)	In this stage of the analysis, socioeconomic indicators were assessed in their distribution across population groups. Chapter 5A. Using STATA version 17, tabulation and graphical analysis were used to compare the mean distribution of socioeconomic characteristics, job competency, skills and other variables based on population grouping variables. The mean was the central parameter traced in the descriptive analysis as the numeric variables (socioeconomic characteristics, hob competency etc) were standardized indexes.	NIDS dataset, wave 1 to 5.
Phase 2: Inferential analysis (2B)	In this stage of the analysis, socioeconomic indicators were used as explanatory variables in the multiple linear regression (MLR) model with digital index as the dependent variable. Chapter 5B. Survey (svyset) methods were used in the analysis of complex survey data and incorporating the survey design (explained in Chapter 4). In the presentation of the results, the coefficients are shown, the T statistic of each variable and its associated p-value (Chapter 5).	

The findings of the study were presented separately, with the results being integrated into the discussion (Chapter 7) of the results, assessing connections between quantitative findings, qualitative findings and the extant literature.

1.7. Anticipated Research Contributions

The anticipated contributions of this study are broadly divided into two sections: (1) contributions to research and (2) contributions to practice.

1.7.1. Contributions to research

The study makes additions to the conceptualisation of digital transformation, explaining DT as tech-based business model transformation, as an open ecosystem of economic and social organisation and as the fourth industrial revolution. The understanding of DT as a tech-based business model transformation and the fourth industrial revolution dominates the academic discussion (Barholomae, 2018; Strohmaier, Schuetz and Vannuccini, 2019; Aly, 2020; Verhoef *et al.*, 2021). In passing over the same ground, the study not only emphasized known concepts but provided more detailed explanations of the concepts and their implications.

1.7.2. Contributions to practice

The study was able to connect the interactions between the physical and the digital divide, explaining how the former influenced and is influenced by the latter and the likely outcomes for society. The discussion was rooted in data based on the experiences of households over a period of time and on the insights of individuals in the frontlines of digital technological development. The linking of micro-level aspects of societies with macro-level anticipated changes in society can provide a basis for the discussion of socioeconomic issues and DT on a more concretely with more informed policy perspectives.

1.8. Thesis Structure

Chapter 1: This chapter aims to provide historical background and rationale for undertaking this study. The research context is highlighted, the objectives and research questions, the theoretical framework and the research design are discussed. The anticipated contributions of the study are stated and the limitations of the study.

Chapter 2: This chapter is an outline of the endogenous growth theory employed as the study's framework of analysis. The theory is discussed, its concepts and implications and finally, the context in which it is applied in this study.

Chapter 3: This chapter presents a critical review of literature on digital transformation. The research gaps are discussed, the conceptualisation of digital transformation, its characteristics, opportunities and challenges. Adaptation to DT is also discussed at the end of the chapter. The central themes in the critical analysis are digital transformation, socioeconomic issues and income distribution as these connect DT with economic participation and the conditions of participation.

Chapter 4: This chapter presents the research methodology, and begins with a discussion of the pragmatist paradigm, the mixed-methods approach, data preparation and analysis and reliability and validity. Ethical considerations are also discussed although briefly as the study utilized secondary datasets.

Chapter 5: Presentation of the results of the quantitative analysis of the national incomes dynamics study. The descriptive analysis is presented followed by the inferential analysis in the form of the linear regression model. Graphs are used in reporting results of descriptive analysis while tables are used in the presentation of the results of the inferential analysis. The results are interpreted and discussed.

Chapter 6: This chapter is a presentation of the results of the qualitative analysis focusing on 4 key themes, the conceptualisation of digital transformation, characteristics of digital transformation, the opportunities and challenges of DT and adaptation towards digital transformation. The results of the thematic analysis are presented, with extracts from the raw data as evidence.

Chapter 7: This chapter is a discussion of the research findings, comparing the findings with the extant literature, and the implications of the findings.

CHAPTER 2: Theoretical framework

2.1. Introduction

In this chapter, a discussion of economic growth theory is provided, with a particular focus on the endogenous growth theory which forms the heart of the theoretical and conceptual framework for this research study. The Endogenous Growth Model (EGM) is explained, with the mechanics of endogenous growth and the implications of the theory on the economy and society. There is no attempt made in this presentation to discuss the deeper assumptions and mathematical derivation of the model, however, the focus is placed on its implication on the economy and economic policy, from which case is made for the application of the model in the present study.

2.2. The Endogenous Growth Theory (EGM)

2.2.1. General Overview of EGT

EGT is an economic theory that argues that economic growth is generated from within a system as a direct result of internal changes and transformations of the general-purpose technological platform through interventions/policies that changes labour-capital combinations that underlie the social relations of production (Romer, 2012). The theory assumes that technological progress depends explicitly on the resources devoted towards the advancement of knowledge, more specific resources devoted to research and development and the more resources devoted to research and development, the faster the knowledge creation process will advance. The change in knowledge is related not only to the resources devoted to it but to the level of knowledge already attained in society. The more is known, the higher the ability to add to the already existing stock of knowledge (Fedderke, 2002). The central propositions of the theory are that the enhancement of a nation's human capital will lead to economic growth through the development of new forms of technology and consequently increased income that brings about changes or improvements in the standards of living (Jones, 2019). Thus, a local economy shapes the technological apparatus, which characterizes the economic and social arrangements of its society given the resources available to the society.

The model is specified as:

$$Y_t = [(1 - a_k)K_t)^{\propto}[A_t(1 - a_L)L)_t]^{1-\propto}$$

In this model, Y_t refers to national income at time *t*, which is determined by combinations of physical capital (K), technological advance (A_t) and human capital (L). As can be observed, the model is multiplicative, which means that the various aspects such as capital (K), labour (L) and state of technology (A), influence each other in compounded ways. Physical capital investment decisions influence the general state of technology, while levels of human capital influence the forms of physical capital investment and technology and vice versa. The more capital invested in the economy; the more income grows at least by the investment of capital in the economy. For example, increased investments in science education other things being equal may increase the number of science qualified personnel in the economy who contribute to the development of technological innovations that can address productivity problems in the economy (Jones, 2019).

Following these propositions, it can be noted that the effective labour (L) and capital (K) investments in the economy/society are those which are associated with the technological arrangements or the general-purpose technology platform (A) existing in the economy or society or that which is envisioned and consistent with the nation's resource endowments or potential resource access. Alternatively, a nation benefits much from technological development that maximizes the use of its abundant resources, or the resources that exhibit sustainable growth. Labour investments that matter is those that are more likely to improve the existing level of technology since technology is developed and applied to solve a nation's productivity problems and so also is capital (Romer, 2012). The use of knowledge is non-rival so both sectors have access to the same knowledge as reflected in the multiplicative relationship, with the production of new ideas dependent on the quantity of capital and labour engaged in research and on the level of technology (Romer, 2012). The multiplicative relationship shows that adding a factor with increasing returns will keep on increasing returns to income, as long as the factor itself is increasing. Take countries like South Africa for example with abundant land and labour resources, if investments are directed at improving the productivity of such abundant endowments, then the transformative potential of such investment is high as compared to when investment is directed at least available resources and competencies. EGT proposes that in the design of the general-purpose technological platform in South Africa, attention much be paid to the role of the abundant resources.

2.2.2. General Observations and preliminary conclusions

Improvements in the general-purpose technology platform shape the nature of physical and human capital requirements in the economy. This is important since the technological arrangements in the economy, shape economic and social relations and hence the forms of labour and capital demand. Consequently, human and physical capital that services and improves the existing general-purpose technological platform remains relevant while, human capital competencies not associated with it, or marginally associated with it, become irrelevant, resulting in the development of unemployed labour and capital, termed structural unemployment.

Another important observation from the model is that the more human capital the general-purpose technological platform depends on, the more employment of human capital will be observed in the economy, the converse is also true. If the general-purpose technology platform is labour intensive, then the majority of income goes to the labour share and so forth. In the context of labour displacement through technological encroachment, DT can result in reductions in labour demand and losses in welfare (OECD, 2017).

2.2.3. Human Capital in the model

The focus on the role of human capital concerns the social relations of production or the social organisation of economic activity and its outcomes; particularly the mechanisms that determine how productivity increases translate to improved standards of living, and developmental outcomes for the population as a whole. According to the EGT, sustainable productivity growth is influenced by internal processes such as human capital investment, innovation and knowledge resources in the economy rather than external uncontrollable factors (Dornbusch, et al., 2013: 80). Paul Romer, one of the pioneers of EGT sought to prove that government policies including investment in research and development and intellectual property law, helps to foster endogenous innovation and fuel persistent economic growth (Romer, 2012). In this model, technological progress, which forms the engine of the economy is made endogenous or determined within existing economic parameters (factors of production/economic resources). Technological progress is generated intentionally by the rational decisions of profit-maximizing agents who respond to market incentives. This model further predicts scale effects from human capital stock, that is an economy with a large total stock of human capital will experience faster growth, and consequently improved standards of living (Romer, 2012).

Thus, the EGM makes an extension of the generic model of growth discussed in the foregoing section, yet focuses on the role of policy intervention that shapes technological advance through investment in research and development directed at solving productivity-related issues to achieve improved standards of living for communities. EGM argues further that productivity improvements can be tied directly to faster innovation and more investment in human capital. To this end, there is advocacy for government and private sector institutions to nurture innovation initiatives and other incentives for individuals and businesses to be more creative such as research and development funding and intellectual property rights (Crafts and Pieter, 2020). The idea is that in a knowledge-based economy, the spillover effects from investment in technology and people produces perpetual returns. Influential knowledge-based sectors such as telecommunications, internet technologies, software development and other high tech industries, platformed by effective social institutions deliberately undertaken have a central role in economic growth (Crafts and Pieter, 2020). The production of new knowledge and ideas depends on the quantity of physical and human capital devoted towards research and on the level of technology. Because existing knowledge discoveries enable the discovery and development of future ideas, the result is technological evolution, this technological evolution will improve the productivity of capital as long as the development of new skills and knowledge sustains technological evolution. As such, human capital becomes the central factor in raising productivity and income.

2.2.4. The basic relationships and concepts

The EGM by arguing that it is the deliberate actions of individual and institutional agencies that bring about economic growth by changing the general-purpose technological platform which shape economic activity, argues for self-sustaining growth within a system (Jones, 2019). Thinking of this argument mechanically means that the central focus of interventionist policy must be on the factors that influence the contributory role of human capital in achieving economic growth. In other words, increased investment in human capital that results in innovations and advancements in the general-purpose technological platform which determines the level of productivity, will increase growth indefinitely since a factor will continue to add to output as long as the supply of that factor is increasing (Dornbusch, et al., 2013: 58). According to Lucas (1988), human capital is meant development in skills levels where the productivity of a single worker can be increased by increasing skills and knowledge levels (Romer, 1994).

Human capital has no diminishing marginal returns, that is the more knowledge capital increases, the more growth can be attained through increases in resource productivity. There are increasing returns to scale from human capital investment, particularly in investment in education, health and telecommunications. To this end, private sector investment in research and development is a crucial source of technological progress (Crafts and Pieter, 2020). Those who invest in human capital and research and development and innovate must have their returns safeguarded. The protection of property rights and patents is thus essential to providing incentives for businesses and entrepreneurs to engage in research and development. Thus, the centrality of human capital as a vital component in economic growth is the central proposition of the EGM. Since ideas are non-rival, there will only be an economic incentive for more people to work in the knowledge sector if there are intellectual property rights such as patents, copyrights and intellectual property (Romer, 2012).

Thus, as long as the economy continues to invest in knowledge development and capital that labour can work with, improvements in productivity and income will be the result. Yet the important knowledge is that which is connected with the general-purpose technology platform or more precisely the envisioned version of it, in this case, digital transformation. General Purpose technologies that influence knowledge creation have an impact on the pervasive weight of such technology in the economy (society) as a whole. This coupled with its use and productivity results in pervasive transformations in the economy.

2.2.5. Explaining Standards of living

Variations in observed standards of living across countries are associated with different amounts of physical capital such as physical infrastructures, human capital and social infrastructure that improves the productivity of human capital (Romer, 1989; Dornbusch, Fischer and Startz, 2013). In EGM, this is linked to the development of new ideas tied to the population of people working in the knowledge sector, with those new ideas improving the general productivity of everyone else in the economy as the stock of ideas increases. Increases in the share of people working in the knowledge sector will increase economic productivity and growth (Crafts and Pieter, 2020). One can observe the influence of communication technologies in the last 10 years and how they have significantly reduced the cost and ease of communication spawning new businesses and providing improved social connectedness.

The EGM normalizes inequalities which are the outcomes of differentials in human capital investment and stocks. It is argued that it is necessary to restrict competition in the knowledge sector to stimulate growth even though this leads to other distortions and disparities in the economy. Improvements in standards of living consequently are not automatic but depend on social capability (social infrastructure) and technological congruence (Crafts and Pieters, 2020). Social capability refers to the ability to assimilate new technology, or the ease with which the general population adopts the new general-purpose technology platform in their economic activity. The absorptive capacity is determined by education, skills and economic competencies such as organizational effectiveness, appropriate business models and training. Social capability thus focuses on social institutions, economic policies and the incentive structure that they imply, which influences the profitability of innovation and investment (Crafts and Pieter, 2020).

The focus of EGM on internal mechanisms that bring about economic growth and improved standards of living, tells societies that they can shape their economic fortunes. It can be seen that countries that lead technological development will maintain income levels ahead of countries that depend on technological diffusion and importation, meaning that growth disparities will always remain regionally and internationally (Cavusoglu and Tebaldi, 2006). The gap between rich and poor countries can remain for indefinite periods because the poorer countries however willing to learn and invest in social infrastructure cannot be expected to be capable of making the same progress in learning as the rich for want of equal means of instruction, equally good models and developmental experience (Cavusoglu and Tebaldi, 2006). A country with a division of labour highly developed enough to support knowledge creation will generate more inventions than a country without well-developed markets. In other words, the scope of education must necessarily change, from broadly adaptive systems (shaping the population to respond to jobs) towards high-end skills such as creativity, critical thinking and entrepreneurship, that promotes the development of innovations. Standards of living that is the general welfare of the society, will be influenced to a greater degree by the capacity of the combined effect of technology and human capital to solve the society's problems, increase the sustainability and productivity of its resources and improve its ability to navigate future changes (Crafts and Pieter, 2020).

This is an important aspect that is not addressed in the DT of societies, while countries need to adapt and change in line with the platform, important adaptation of DT must be influenced by the society's existing resources and how they can be transformed to bring about improved standards of living. This stems from the primary ideas that shape digital transformation, which is to solve the problems of countries at the leading edge of technological development

(Ristuccia and Solomou, 2014). According to EGM, there is no perfect competition across the board, but imperfect competition particularly in high-income knowledge-generating sectors. There are increasing returns to knowledge creation, that is to human capital which allows for the creation of new ideas. It is these increasing returns to investment over a broader range of capital goods including human capital that does not necessarily diminish as economies develop (Cavusoglu and Tebaldi, 2006). Spillover of knowledge across producers and external benefits from human capital is central to productivity growth but only because they help avoid the tendency for diminishing returns to the accumulation of capital. There are positive spillover effects of knowledge creation because knowledge cannot be completely patented or hidden from economic agents. In that sense, knowledge can be considered a public good. (Crafts and Pieter, 2020).

Scale effects predict that countries or regions with larger economies grow faster because access to larger markets allow profit-maximizing firms to produce a large number of intermediate goods which raises productivity, expands the possibilities of production and generates growth. Large economies can allocate large reserves towards research and development which generates technological progress and promotes growth (Crafts and Woltjer, 2020). There is, therefore, no realization of economic convergence, rich countries remain rich and poor countries will remain poor relatively. The model is thus endogenous in the sense that rational utility-maximizing agencies endogenously determine human capital accumulations. Lucas (1988), model predicts that initial levels of human and physical capital are important in explaining cross country differences in per capita output due to the presence of scale effects of human and physical capital. In other words, economies that are initially poor will remain relatively poor through their long-run rate of income growth will be the same as that of initially wealthier economies (Crafts and Pieter, 2020). It can be reasonably argued that under digital transformation, smaller countries must necessarily expose themselves and weather the challenges of globalisation if they would seek to increase their income through increased trade and international exchange, with implications for national economic welfare. This is because of the need to increasingly participate in the larger markets.

Given interventionist policies, the model can be expanded to imply that population growth is not necessarily a developmental problem. Rather, with the right policies and effective social infrastructure, population growth can lead to increases in the stock of knowledge, thus raising the income and output of the economy indefinitely. Thus, it is not population growth per se but the labour force and the stock of skills and knowledge relative to the evolving nature of the general-purpose technological platform (A_t), which determines output and income in the economy for developmental outcomes (Romer, 2012). The higher the number of people making knowledge discoveries, and applications, the more knowledge creation and discoveries that are made. The focus on population growth thus shifts towards the mechanics that underlie skills and knowledge development in the population. Thus, when more discoveries are made, the stock of knowledge grows faster and so (all else equal) output per person grows faster. These conclusions are quite radical that population growth is not the problem but the mechanisms that equip the population for knowledge production and skills development since increasing knowledge production increases output.

2.2.6. Income distribution and inequality

The model also explains the nature of income distribution within an endogenous system, by focusing on how endogenous technological change brings a sustained change in income growth and the consequent income distribution. Technology has a public good component as well as a private good component. Those parts of technology products that have greater marginal social benefit can be privatized to encourage rational economic agents to undertake purposeful technological innovation (Romer, 2012; Jones, 2019). It was also stated that technological advance is the outcome of deliberate investment in knowledge creation and development (Jones, 2019). This is the reason that motivates societies to create institutions that agglomerate individuals who can think and make use of information and with the capacity to add to the accumulating stock of knowledge. However, the importance of an institution and its capacity to create useful knowledge can be measured based on the consequent applications of the knowledge thus created concerning the existing problems within the society.

Knowledge itself has a pure public good characteristic in the sense that spillover effects are non-excludable, prevalent in contemporary society where there is increased documentation and access to research. The consequence of this is that economic agents do not have the opportunity to internalise the full marginal benefits which attach to a given piece of capital equipment. Since some of the benefits spills over to increase labour efficiency throughout the economy, if the proportion of benefits that are captured is not sufficiently high to compensate initial investment in research and development in the creation of that knowledge, the result is private under-investment in knowledge creation. The consequence is that there is less incentive to invest in technological development and hence low productivity. In developing countries and emerging economies, there is thus a strong role for government-directed investments in the co-creation of knowledge resources through partnerships with the private sector (Fedderke, 2002; Spear and Young, 2016).

2.2.7. Implications for socioeconomic welfare for society

To overcome this challenge, the government subsidizes some sections of knowledge production and development, through investments in developing human capital, specific infrastructures and some areas of production; hence raises the incentive towards private investment in technology development. In this manner, some aspects of society benefit, thus setting them apart from others, specific individuals are given a deliberate head start. Thus, inequality in income, human capital development and technology ownership are intrinsically built within the model that brings about technological change and consequently income growth. Those who capture the benefits early advance qualitatively and materially more quickly than those who do not, even though the increase in knowledge and technological change brings about increased welfare throughout the economy. This outcome is also dependent as proposed earlier on the level at which a given economic agent is connected to the general technological platform (Cavusoglu and Tebaldi, 2006). Thus, widening income disparities are to be expected and normalized among diverse groups of economic agents, with the highest income going to various groups of technological developers and financiers, then towards those whose human capital is useful or relevant to the existing general technological platform and evolves with it, and lastly towards those marginally connected with the platform, who experience losses in welfare.

While redistributive mechanisms through societal institutions can allocate income, this structure of returns and benefits will ensure increasingly widening economic disparities. It can be proposed that long-run income inequality can be corrected only by a consistent change in the apparatus that influences how individuals extract value from the evolving general-purpose technology platform, and also through changing the focus and definition of welfare. Technological change consequently generates increases in wage inequalities because technological change is biased towards certain skills, competencies and specialisations, as such it reveals and enhances new differences in abilities among workers across and within population groups (Jones, 2019). While the divergence between demand for skilled labour versus unskilled is expected, it must be noted that the relevant human capital is that which is connected with the evolving nature of the new technology. Following from this it can be preliminarily asserted that addressing long-run structural inequalities in economy and society will require institutional capacity that addresses these biases that marginalize vast sections of the population from the centre of economic activity within the evolving general technological platform (Jones, 2019). This is the general assumption concerning DT at the heart of this study, that there are sections of the society that will experience welfare losses through exclusion and marginalisation.

Since the EGM places emphasis on the role of human capital, that is people driving economic growth through their knowledge, skills and competencies, the emergence of poverty and poverty traps can be understood. The decisions of people, given their incentives and opportunities in human capital accumulation, drive economic growth and the level of income they can access from it, and as such, their observed standards of living. Poverty is such an outcome of conditions that relegate people to sectors where they are least connected with the general technological platform or disconnected from it. Poverty especially that of long duration can be alleviated by increasing productivity of lower levels of education and linking education towards the existing or envisioned general-purpose technology platform.

2.3. Applying the model to the present study

2.3.1. DT as a General Purpose Technology Platform

$$\Delta Y_t \ = [(1 - a_k)\Delta K_t)^{\propto}[\Delta A_t(1 - a_L)\Delta L)_t]^{1-\propto}$$

General-purpose technologies have the effect the larger the weight of embedded technologies in the economy as a whole. This coupled with its use and influence on productivity results in pervasive changes in the economy and society. DT has been argued in the literature to effect changes in three key technological platforms, energy infrastructure, telecommunications and internet and transport and logistics infrastructures (Gefter, 2010). The convergence of these three technologies is argued to bring about a new platform for a social organisation of economic activity. According to the model, income changes (ΔY_t) are the result of technological change (ΔA_t), capital (ΔK_t) and labour (ΔL_t). While the mechanics of the model can be complicated particularly the mathematics which has been avoided in this discussion, the abstract model's principles form the basis of the model's application in the present work.

This study takes DT as a general-purpose technology platform, which will determine the new shape of economic and social arrangements. Using the EGT framework, the platform predicts a need for change in the constituent parts of the society's income-generating mechanisms. There is a need for new skills, new forms of physical and intangible capital investments that align with the new arrangements, the connection of which shapes new forms of income distribution and redistribution. Drivers of DT which include technologies such as artificial intelligence, 3D printing, robotics, robotic process automation, Big data technologies, nanotechnology, autonomous processes and so forth, are technologies requiring both new forms of capital and new human capital skills (OECD, 2017; Sousa and Rocha, 2019). The important characteristic of digital transformation is the rapid change in the general-purpose technological platform, which invokes rapid changes in human and physical capital requirements. This understanding is established in empirical literature concerning internet-based technologies. In an empirical paper, it was concluded that the impact of new general-purpose technologies on economic growth typically takes a longer time horizon to materialize with Information and Communication Technology (ICT) being the exception (Crafts and Pieter, 2020).

In applying this model, it is assumed that income is determined by the interaction of the general-purpose technology, human capital, and physical capital investment in the economy. If a larger proportion of the population has the requisite skills and competencies to participate in the economy, then they experience welfare gains and vice versa. However, the existence of such competencies among the population groups depends on their access to facilities and institutions for human development and training, termed the social infrastructure. Individuals and their organisations both private and the public can intervene through policy and shape the development of these competencies so that the outcomes of transformative change can be shaped and regulated. However, the capacity of the individuals and their organisations to accomplish this is influenced by the initial conditions of their societies, such things existing social and economic organisation, state of social and economic infrastructures, regional similarities and disparities, distribution of economic activity, income distribution mechanisms and the level of participation in economic, social and political affairs among other considerations. These aspects are examined in detail in the literature review (Chapter 3).

The key digital innovations and technologies driving DT, particularly artificial intelligence, robotic process automation, robotics, big data, 3D printing etc., have specific physical capital requirements and associated human capital needs which rapidly changes the social and economic relations of production and overall economic activity (Gölzer and Fritzsche, 2017). These have consequences for the existing social infrastructures, human capital stock, physical capital stock and stock of knowledge in the society engendering transformations in the economy and society. The attendant social welfare is expected to be a consequence of the changed social and economic relations of production which presently are still evolving and unknown (Reddy and Reinartz, 2017).

It is still assumed that economic agents will engage in economic activity, particularly technological change and innovation in response to market incentives. However, it is expected that knowledge creation that brings about technological change is that which is specifically devoted to knowledge creation directed at technological development. In other words, technological change can only be realised if human capital is devoted to knowledge creation that is aimed at the development of technology (El-Darwiche *et al.*, 2013). More human capital devoted to technological research will increase the growth rate of the stock of technology in the economy. Furthermore, knowledge production is technological and human capital intensive with less reliance on either capital or unskilled labour. Thus under conditions of increased technological growth, the growth rate of economic output, in the long run, will come to equalize the growth rate of output, which follows from effects of human capital compounded by the productive efficiency of the human capital (Fedderke, 2002; El-Darwiche *et al.*, 2013).

Thus, it can be expected that long-run income disparities will be explained by differences in human capital endowments particularly those endowments highly relevant to the existing technological stock and that efforts towards socioeconomic equity should focus on improving the human capital balance of the economy across the population. It is human capital and specifically investment in human capital employed in knowledge production that not only serves to raise the production of knowledge but in so doing expands the range of physical capital which is at the disposal of production of the final output. Thus, there is a need for a trade-off for present consumption to increase future welfare improvements. Within this trade-off, the decision-makers should subsidize human capital investment, particularly human capital engaged in the research and development of technology (Hilbert, 2020).

The focus is not on the size of the market in terms of labour that matters, however, it is the human capital content of the labour market that is crucial to the long-run growth opportunities of a set of markets. This implies that the rate of return to human capital will prove to be higher where human capital is most abundant, that is, in the presence of labour mobility, the implication is that highly endowed human capital will move towards regions where there already exists extensive human capital. The policy implications are in order, if a country is lagging in the accumulation of human capital it is likely to remain behind. Countries ahead in technological development will remain ahead and gradually advance beyond lagging countries, and human capital emigration will continue to plague less developed regions (Crafts and Woltjer, 2020; Hilbert, 2020).

It is these mechanisms that influence human capital investment and growth that have a deterministic influence on the welfare of regions in the long run. Poor regions are poor because they are poorly endowed with human capital that improves their productive apparatus, the general technology platform. The interventions designed to correct the situation of low human capital stock, particularly investments in education merely serves to benefit already wealthy and endowed regions, further accelerating their growth and entrenching growth differentials (Fedderke, 2002). Since low human capital endowed regions will persistently experience emigration of highly skilled labour, the consequence is that at low levels of human capital accumulation, there may not be a critical mass of human capital to generate adequate returns from the generation of new knowledge, let alone harness existing knowledge for local development. This pattern is observable across countries and is testable across regions. The human capital stock that remains may not be efficiently allocated where it has the highest impact on long term growth. Given these considerations, low human capital regions do not only have market incentives to worry about, but they also have to design better and more effective mechanisms to retain the human capital stocks they have at their disposal.

2.4. Chapter Summary

The foregoing discussion has focused on the endogenous growth model with the application of the model to this study taking DT as a general-purpose technology platform generating new arrangements of production, employment and economic relations. According to the theory, technology is developed through deliberate policies and intervention through human capital that shape the technological apparatus of the economy to achieve increased productivity, income growth and improved standards of living. The socioeconomic effects of DT using the concepts of endogenous growth depends on the factors that feature prominently in the general-purpose technology platform. If it is centred around labour and human skills, then increased employment results, however, where capital displaces labour, the income realized increases the capital share while the labour share is significantly reduced with resultant income inequalities in the economy and society. Societies that devote more resources to knowledge production create knowledge and technologies faster than those that do not, thus distinguishing technology developers from net technology consumers. And this is the central thesis around the expected outcomes of DT on socio-economic welfare.

CHAPTER 3: Review of Extant Literature.

3.1. Introduction

The discussion focuses on DT and the factors that determine how individuals and societies can participate in a transforming environment. The central argument of the discussion is based on the notion that a society's socioeconomic welfare is determined by how the society's individuals are connected or maintain their connection with the evolving general technology platform and adapt to (Jones, 2019). The gaps informing this research study are discussed, followed by the literature on DT and its socioeconomic outcomes.

3.1.1. Summary of critical review of literature informing gaps in research

Table 2: Literature summary of gaps in extant literature.

Author	Country	Title	Source	Findings
(Gabryelczyk, 2020)	Warsaw, Poland	Has Covid-19 accelerated digital transformation? Initial lessons learned for public administrations.	Journal article	Increased digitisation has been the outcome of the covid-19 pandemic and public administrations are undergoing this transition although ill-equipped. There is a need for a broader discussion on what constitutes digital transformation which presently is a challenge for both researchers and practitioners.
Venkatraman, N (2017).	India	The Digital Matrix: New rules for business transformation through technology	Book Chapter	Guideline for successful digital transformation for businesses and advocates for the need for a theory on how digitalisation transforms companies and industries as the basis for creating organisational strategy. Focuses on business and digitisation and not the processes of digital transformation.
(Verhoef *et al.*, 2021)	London	Digital transformation: A multidisciplinary	Journal article	Digital transformation is ubiquitous with visible impact seen in new business models.

		reflection and research agenda		Attention in the academic literature has been limited with the recent focus moving towards digitisation, digitalisation and digital transformation. Businesses have focused on digital change. Need for focus on digital transformation on a broader level, using a multidisciplinary approach.
(Lamberton and Stephen, 2016)	USA	A thematic exploration of digital, social media, and mobile marketing: Research evolution from 2000 to 2015 and an agenda for future inquiry	Journal Article	Digital change is transforming marketing and consumer management through increasing access to more nuanced user data. There is increased digital integration in business models changing business and customer relationships. Future research can focus on emerging patterns of change as the transformation continues, which can be useful for researchers and practitioners.
(Acemoglu and Restrepo, 2019)	Germany	Automation and new tasks: How technology displaces and reinstates labour.	Journal Article	Framework for understanding effects of automation and other technological changes on labour demand as a guide to understanding labour market dynamics in the USA. Focuses on technology-induced unemployment and business efficiency.
(Manda and Ben Dhaou, 2019)	South Africa	Responding to the challenges and opportunities in the 4th Industrial revolution in	Journal Article	Digital transformation has economic benefits for developing countries, given the existence of requisite capacity for adapting to digital transformation.

		developing countries		The study used document evidence and review of literature as sources of data. Potential employment loss, infrastructure challenges, and skills challenges were broadly stated challenges without an investigation of the nature of such challenges and their patterns.
(Manda and Backhouse, 2017)	South Africa	Digital transformation for inclusive growth in South Africa: challenges and opportunities in the 4 the industrial revolution	Journal Article	The study uses an interpretive case study in understanding social, economic and contextual issues surrounding the implementation of regulative and other mechanisms for promoting digital transformation. The conclusion for a need for institutional capacity is based on inference from analysis of studies on socioeconomic issues. Thus, the study focuses on the role of government and other institutions in promoting inclusive digital transformation, however, does not focus on the dynamics of the individuals within South Africa.
(Strohmaier, Schuetz and Vannuccini, 2019)	Germany	A systematic perspective on socioeconomic transformation in the digital age.	Journal Article	The study used a structural decomposition framework on over 10 years of economic data on Western and Asian countries to assess capability to absorb technology change. The structural decomposition enabled an analysis of structural change induced by technological change

				over a longer time horizon. The present study follows this method with a focus on individuals across a longer time horizon.
(Balsmeier and Woerter, 2019)	Switzerland	Is this time different? How digitalization influences job creation and destruction.	Journal Article	The article investigates the impact of digitalisation on job creation and destruction and assesses how processes of digitalisation differ from emerging technological transformation. Increased digitalisation benefits skilled workers more than low-middle skilled workers. Focus on digitalisation, however, is limited particularly when human processes that shape skills accumulation are considered. No consideration is given to these in the article. Focus is also placed on purely economic issues as roles of labour and technology.
(De Ruyter, Brown and Burgess, 2018)	New York, USA	Gig Work and the Fourth Industrial Revolution: Conceptual and regulatory challenges.	Journal Article	Digital transformation or the fourth industrial revolution is changing the composition of skillsets of the workforce. Not only labour displacement and technology-induced unemployment but a shift towards different jobs and new skillsets Work will be technology-mediated and based on information and communication. This study assesses the skills composition of the

				workforce and the forces that shape skills accumulation (socioeconomic characteristics).
(Misuraca, Pasi and Viscusi, 2018)	Western Europe	Understanding the Social Implications of the Digital Transformation: Insights from Four Case Studies on the Role of Social Innovation to Foster Resilience of Society	International Conference Paper.	The article focuses on the role of ICTs in restructuring labour markets and social protection systems. ICTs are capable of solving institutional challenges at a large-scale guaranteeing people's well-being such as promotion of employment, social insurance and social assistance. ICTs and digitalisation can also change social structures leading to adverse socioeconomic development and welfare loss requiring both institutional change and human development to avoid. Experiences of advanced Western European Countries.
(Ndemo and Weiss, 2017)	Nairobi, Kenya, Africa	Making sense of Africa's emerging digital transformation and its many futures.	Journal Article	Digital technology integration in African societies is on the rise and accelerating. However, adoption rates mask inequities that result in digital economies operating on the margins of African societies, without attendant benefits being experienced in advanced countries. There is a need for an understanding of the broader social processes, organisational and cultural environments that can shape the

				transformative effect of digital technologies.

3.2. Gaps identified in the literature

In this section, the inadequate treatment of the subject area of DT and socioeconomic welfare in the literature is discussed. The limited consideration of the micro-level effect of DT on socioeconomic welfare is discussed next which areas are the proposed gaps within which this research study is positioned.

3.2.1. Inadequate treatment of the subject in the literature

Despite the ubiquity and visible impact projected of digital DT on income distribution, with projections of a very unequal distribution of welfare gains and losses, little attention has been paid to these issues in the academic literature (Venkatraman, 2017; Verhoef *et al.*, 2021). It is only recently that attention has started to be given to topics of digitalization, digitization and digital transformation, however, other factors such as the current covid19 pandemic have accelerated the pace of DT whose socioeconomic implication is not well understood (Gabryelczyk, 2020).

Since DT is being driven by business innovation, the academic literature has tended to focus on digital change within specific business sectors. Market researchers have focused on digital advertising and social media change using tools that sought to give insight into aspects of business value that can be improved through digital technology adoption (Lamberton and Stephen, 2016; Kannan, 2017); and business gains from consumer data embeddedness (Verhoef *et al.*, 2017). In the management literature, the focus has been on the conceptualization, operationalization, and renewal of digital business models (Foss and Saebi, 2017). Finally, the innovation literature has focused on technical developments concerning the development and application of technology and business value (Nambisan *et al.*, 2017).

Thus, the debate on DT within the academic community has paid little attention to socioeconomic issues. The consideration of DT in business has assumed a functional siloed type profile, with limited scope for multi-disciplinary engagement since the focus is almost exclusively directed towards business efficiency. It is necessary to bring insights from various disciplines to make sound multidisciplinary contributions concerning how to respond to digital technologies and implement digital change that will benefit organisations and society participants.

The focus on organisations also seems to mirror the general positivity with which DT is viewed in conventional economics. According to conventional economic understanding, technological progress has generally been associated with an increase in wealth and job opportunities in the long-term adjustment process (Brynjolfsson and McAfee, 2014; Kaivo-Oja, Roth and Westerlund, 2017). The effect of technology in this strand has been exclusively economic on job destruction, technological transformation and productivity without a focus on micro-level aspects of socio-economic change. A literature review on the effect of technologies conducted by the Chartered Institute of Personnel and Development suggested little systematic evidence detailing the impact of technologies on workers (Tohanean, Toma and Dumitru, 2018). The study found out that much of the research was based on speculation and anecdotal evidence with existing evidence suggesting that technology is augmenting what economic agents are doing and enabling scope skills reconfiguration. The returns to DT postulated do not account for differences among countries and individuals within their specific geographies and are thus not too useful for understanding context-based developmental issues in countries at the lower end of technological development.

3.2.2. Limited treatment of socioeconomic issues

Existing evidence concerning the disruptive effects of DT on labour market outcomes has been quite speculative particularly in developing countries (Verhoef *et al.*, 2021), with most of the research focusing on economies of the developed world (Westerman, Bonnet and McAfee, 2014; Acemoglu and Restrepo, 2019; Chinoracký and Čorejová, 2019). This has been attributed to a lack of data on the issue (Pierre Celestin, 2020), and limited research on socio-economic issues (Verhoef *et al.*, 2021). The general narrative however is that similar to the historical occurrence of technological transformation, DT positively affects the outcomes for those with better education and training. This study examines how these effects occur and the factors that influence an individual's stock of competencies that generally improve their prospects in a transforming environment.

Productivity statistics provide a limited understanding of fundamental changes in labour markets (Brynjolfsson and McAfee, 2014). According to these authors, this stems from the fact that the effects of automation are normally concentrated in low-skilled occupations. The employment effects of process innovations have been less clear in empirical research in developed countries, much less in developing countries. Moreover, studies have not used industrial data to measure and discuss the employment effects of DT or innovation. In a paper assessing productivity, employment and DT in developing countries, the authors concluded on the possibility of mass unemployment and proposed the existence of structural change in unemployment. The analysis however was restricted to the effects of DT on the aggregate level of employment, with no focus of analysis on microlevel impacts such as a change in the pattern of available newly created jobs and what that implies for underlying societies (Aly, 2020).

It was suggested that future research should investigate how the integration of government, industry, higher education and civil society can be instrumental in fostering social cohesion to address social, economic, governance and other challenges threatening inclusive DT (Manda and Backhouse, 2017a). This study together with similar studies (Manda and Backhouse, 2017; Misuraca, Pasi and Viscusi, 2018; Strohmaier, Schuetz and Vannuccini, 2019; Vakirayi and Van Belle, 2020), have focused on broader socio-economic issues, and extended the doctrines of economic inclusion and development without exploring the micro-level dynamics that underlie the capacity of individuals to experience positive socio-economic welfare.

The existing predictions of the effects of DT on economies and societies are very dependent on access to and application of technology, the industrial configuration of the underlying economies being investigated, policies surrounding employment, investment and research and the infrastructure available to support new technologies (De Ruyter, Brown and Burgess, 2018). These many scenarios, analyses and predictions are fundamentally based on the characteristics of very advanced economies, and there is a substantial degree of doubt that the impact of such labour market and living standards exhibit the same pattern and significance in developing economies. This is because these countries have socioeconomic characteristics vastly diverse from those of the advanced industrial countries in the developed world.

In another study focusing on inclusive growth in South Africa, the authors described the opportunities and challenges of DT broadly and concluded that future research will need to investigate possibilities for partnerships among government, industry, education institutions and civil society on how social cohesion can be fostered. This social cohesion will be useful in addressing social, economic, governance and other challenges threatening successful inclusive DT (Manda and Backhouse, 2017). In undertaking an analysis of DT and socioeconomic welfare in this study, a presentation of the characteristics and outcomes of DT and effects on socioeconomic outcomes is assumed to provide a clear basis for understanding the partnerships and nature of cohesion that is required to provide a basis for inclusive growth in a digitally transforming society.

3.2.4. Directions in this study

In Africa, digital technologies remain an emergent phenomenon, with minimal marginal impact on the economies. The realization of the potential of DT will require not only increased innovation and widespread adoption of technologies but the reconfiguration of the underlying social structures in which they operate (Ndemo and Weiss, 2017). The effect of technology on socio-economic issues has not been examined at the micro-level, focusing on the recipient societies and individuals so that robust policies and interventions can be made. This study will contribute to this micro-level analysis.

Central considerations in evaluating the effect of new and emerging technologies on employment and income in the future lie in understanding the connection between new technologies, innovations, employment and the mechanisms that destroy forms of work and those creating new forms of work and how these interact (Nübler, 2016). Such an approach enables policymakers to account for different types of innovations, in the short term as well as in the long term, revolutionary and evolutionary adjustment processes, the role of economic, social and political forces with the complex non-linear and uncertain nature of the processes. Research instrumental in directing policies will require micro-level analyses of DT and the underlying dynamics of the recipient societies, which has not been carried out sufficiently in the empirical literature. The contemporary discourses at the international level, even the ones constituting the qualitative data used in this research study are learning processes and more so particularly as far as developing countries are concerned. These discourses examine technological transformation against rising tensions between established institutions and the economy, unintended outcomes of technological transformation and the attendant shift in the development debate from productivity growth towards structural transformation.

Broader structural transformation marginalizes vast segments of the population, and create economic and social inequalities because the economic forces that shape structural transformation are unevenly distributed. Thus, inequalities will stem from the distribution of research and development, the role of the state, innovation, investment, structural transformation and employment generation. The current state of technological development, research and development in science is biased against women and children and the poor margins of society who do not participate in the frontlines of innovation and technological development (Webster, 2014; Rosser, 2016). The contemporary debates have not broadly investigated these issues in the promotion of DT and its attendant structural implications upon societies. Thus, DT will potentially introduce new forms of inequalities heightening already existing ones and more so in countries with already high economic and social inequalities like South Africa (Branson and Leibbrandt, 2013). The distinction between those with access to digital technologies and those without will likely be exacerbated for all important economic fundamentals such as skills and education (Manda and Ben Dhaou, 2019).

While the role of geography in poverty analysis has been advanced in various studies (Addison, Hulme, and Kanbur, 2009; Aue and Roosen, 2010; Banovcinova, Levicka, and Veres, 2014), systematic research on poverty which considers digital inequalities is presently insufficient. This must not be confused with research studies that have paid attention to the spatial identification of poverty-stricken regions or poor populations and the underlying poverty mechanisms. What is not known is how interaction with digital technologies at the scale of DT will likely affect these spatial districts, which knowledge can be instrumental in informing policy positions and finding pathways of mitigating the negative developments associated with pervasive DT (Zhou and Liu, 2019; Langley *et al.*, 2021). This study underscores the effect of spatial disparities and how DT influences poverty outcomes in the face of such disparities in both economic and social development. The discursive platform on DT for the past five years has been preoccupied with much interest in the new concepts associated with this systemic change in social and economic organisation, which will radically alter the way people live, work and interact. However, there is a lack of understanding concerning the mechanisms through which such technologies will affect societies, businesses and their contribution to these societies (Langley *et al.*, 2021).

3.3. DT and socioeconomic conditions.

In this section of the discussion, the focus is placed on understanding DT and its processes with a specific focus on the processes and mechanisms through which DT affects socioeconomic outcomes for individuals and societies. The discussion centres on three key aspects, understanding digital transformation, the drivers of DT and the impact of disruptive technological change on unemployment.

3.3.1. Understanding digital transformation

Three interconnected concepts have been used interchangeably and these defined here are digitization, digitalization and digital transformation. Digitization refers to the encoding of analogue information into digital format to enable computers to store, process and transmit information. Empirical research also associates digitization with the transition from analogue to digital tasks or integration of Information technology (IT) with existing tasks. Digitization thus defined can be seen in applications such as ordering processes, digital surveys, and conversion of internal and external organizational documentation processes without transforming the value creation services (Verhoef, et al., 2019). Thus, digitization does not affect relations of production as it does not change value-creating activities while improving information storage, access and reproduction thus improving productivity to those working with IT technologies.

Digitalization refers to the use of IT or digital technologies to alter existing business models and processes (Burchardt and Maisch, 2019). Digitalization, therefore, results in sociotechnical changes with digital artefacts which were not possible to employ without digital technologies. IT is the key enabler in a digitalization process to seize new business opportunities by changing existing business processes viz, communication, distribution, or business relationship management (Verhoef, et al., 2019). Thus, firms apply digital technologies to optimize existing business models by enabling more efficiency between processes or by creating additional customer value. Thus, digitalization is most pervasive in business processes where IT-based re-engineering of existing business processes is envisioned (Burchardt and Maisch, 2019). Digitalization induces socioeconomic change, laying the foundations for a fully-fledged technological revolution thought of as interrelated radical breakthroughs and forming constellations of interdependent technologies (Strohmaier, Schuetz and Vannuccini, 2019). Digitalisation was seen to be occurring in advanced industrial countries since the opening of the second decade of the 21st century (Perez, 2013). A characteristic of this period was the dominance of entrepreneurs dominating financial capital with the emergence or strengthening of institutions safeguarding market functionings and social well-being. Digitalisation is argued to carry with it creative destruction which affects societies in costly ways (Perez, 2013; Strohmaier, Schuetz and Vannuccini, 2019). Digitalisation thus lays the foundation for pervasive digital transformation.

DT is pervasive and describes a situation of a complete overhaul of business organizations, societies and production relations (Pollitzer, 2018; Eller *et al.*, 2020). DT restructures entire organizations and ways of doing business and goes beyond digitalization—the change in simple business processes and tasks. It is a reconfiguration of business models and processes to change the logic of the firm and its value creation process (Golzer and Fritzsche, 2017). DT is the outcome of what is termed in economics parlance, a general-purpose technology, one that can transform itself, platforms wider social and economic transformation through its capacity to progressively branch out and boost productivity across all sectors and industries

(Muhleisen, 2018). Thus, DT, as conceptualized and understood in this study, refers to the pervasive technological transformation that fundamentally transforms existing socio-cultural, economic, political, environmental and legislative structures underpinning existing relations of production and economic organization, requiring a shift in modes of production and economic management (Sousa and Rocha, 2019).

3.3.2. Implications of digital transformation

DT is considered a firm-level initiative driven primarily by a quest for productivity improvements and involves a transformation of business models through the implementation of digital technologies (Santos, Batista, and Marques, 2019; Eller *et al.*, 2020). The government has been instrumental in its ability to make extensive investments in various sectors and building the infrastructures that provide the foundations on which private organisations build their technologies, and this has frequently been done with consultation of the private sector or to promote entrepreneurial development (Gefter, 2010). There is a rearrangement in the processes of businesses with changes in the logic of firms and value creation processes (Gölzer and Fritzsche, 2017). Firms pursuing DT search for and implement business model innovation, which means they require skills that enable them to achieve the intended changes to the business. Incumbent firms do face challenges and constraints when searching and implementing business model innovation for DT and are forced to address conflicts and trade-offs between existing and novel ways of undertaking business (Christensen, Bartman and Van Bever, 2016). To compete in an era of digital transformation, firms require digital assets for data storage, information and communication infrastructure and associated technologies to allow for artificial intelligence (AI), machine learning, the internet of things and robotic processes. These advancements enable the firms to leverage existing knowledge bases and other resources to generate more value for customers (Verhoef *et al.*, 2017).

Within this framework of transformation, firms create big data teams that comprise analytical, data management, data visualisation, business strategy and business skills. With the big data analytics capability in place, continuous training initiatives need to be established and operationalised to update skills, since with increased technological innovation or increased digitalisation of economic and social activity demand for high-end skills increases (Kübler, Wieringa and Pauwels, 2017). In South Africa, the working-age population based on recent population estimates stand at 59.17 per cent, with the unemployment rates fluctuating around 27 per cent (Diego and Munthree, 2020). Given these statistics, and allowing the active population to be dissected into different types of skills groupings say between low skilled, average skilled and highly skilled individuals based on occupation and education Then, under digital transformation, in-training skills and upgrading is available to highly skilled and employed individuals, low skilled occupation are at high risk of displacement while the unemployed, underemployed, the displaced and those without skills, will have to seek pathways to skills upgrading to participate under new socio-economic organisation (Sousa and Rocha, 2019). Depending on the pace of digital transformation, the demand for high-end skills will evolve faster benefiting those companies with in-training and continuous learning systems, and the individual most likely to benefit while that outside employment will have to bear the costs of education and skills upgrading under conditions of unemployment. This is the evolving dynamics in the contemporary South African economy and its institutions (Mavunga and Cross, 2017; Kayembe and Nel, 2019; Mhlanga and Moloi, 2020). Thus, the implications of DT are gross social inequalities in education and economic participation, given the initial conditions when the processes of transformation begin to take place.

The processes of transformation when they occur do trigger massive shifts in the existing ways of production and exchange or delivering of services. Consider the taxi industry since the introduction of platforms such as Uber, Taxify and In-driver, which have removed the need for call operators who allocated taxis on request, while making use of non-professional drivers delivering the services. In countries where digital technologies such as driverless cars become streamlined, such drivers might see their wages decline or their services displaced, with income shifting to those who invest and own self-driving cars. Thus, shifts in income distribution are associated with DT while the burden of upgrading and skills development shifts to the individuals who are increasingly vulnerable in an environment of constant change and evolution (Manyika, et al., 2017; (Afonasova *et al.*, 2019). This example shows that the existing channels for social and economic organisation and the individuals accommodated within existing arrangements are being replaced and displaced. In sum, full-scale DT will impact logistics and value chains, production networks and work relations, skills requirements and processes supporting trade. These will call for adaptive change in societies requiring remodelling existing regulatory frameworks and creating novel ones with major implications for sustainable development goals in particular since the majority of the developing countries are incapacitated and inadequately prepared to capture opportunities emerging through DT (Pollitzer, 2018). As argued earlier, these outcomes necessitate new research to increase mapping and understanding of relationships between digital technologies and how these influence socio-economic development and welfare. Empowered with this information countries can make policies and establish mechanisms to develop capabilities that improve societal adaptation to pervasive change, generating this information is what this research intends to achieve.

3.3.3. Drivers of digital transformation

DT is driven by a range of innovations in technological development and application, in internet communication, energy and transport and logistics, the convergence of which has brought about the creation of a general-purpose technological platform (Verhoef, et al., 2019). These technologies and applications include advances in computing power and big data technologies (Gunther, et al., 2017), robotics and artificial intelligence (Dafoe and JIA, 2019), the internet of things (IoT) platforms and technologies (Benamar, et al., 2020), advanced materials and biotechnology, advanced manufacturing and 3D printing, mobile internet and cloud computing (Schwab and Samans, 2016), energy internet technologies (Ustundag and Cevikcan, 2018) and advanced robotics and autonomous transport (Calvao and Thara, 2019). Essentially the driving force in DT is the increasing adoption of digital technologies into economic and social interactions aimed at improving economic efficiency and productivity (Kaplan and Haenlein, 2019). In more advanced countries, DT has been linked with technologies such as artificial intelligence, predictive analytics, distributed ledger technology (blockchain) and the internet of things. These countries have been at an advanced stage in the development and application of these technologies (Ershova and Hohlov, 2018). What is important about these technological advancements and their applications that make DT inevitable is that they are viewed as solutions to sustainability problems.

There is a group of technologies viewed as innovation accelerators including solutions such as the internet of things, robotics, 3D printing, artificial intelligence, augmented and virtual reality, security, nanotechnology, blockchain, big data and cloud computing (Ulas, 2019). These technologies are seen as providing solutions in different areas of society, from the environment, healthcare, public governance, information use and storage and national security, and thus are increasingly being adopted bringing with them the transformation of the existing social and economic arrangements.

The expansion of information and communication technologies and the emerging role of information analysis in both business and government with dependency on the capability to integrate digital technologies and analytics have been important (Manda and Backhouse, 2017). Broader access to information in various aspects of economic, social, political and cultural life has led to increased recognition of the critical role of smart ICTs as tools for facilitating public management, socioeconomic transformation and inclusive economic development (World Economic Forum, 2016). In 2016, the Indaba Manufacturing conference in South Africa brought together academic institutions, businesses, government, and industry to find pathways in taking advantage of the emerging digital transformation. Among the major strategies was the need for increased adoption in the use of advanced information and communication infrastructure technologies in the industry, government, and society as requirements for a digitally transformed society (Lom, Pribyl and Svitek, 2016). In this strand, the use of cloud computing technologies, the internet of things, and smart logistics were proposed as key technologies that will move the country's economy and society forward (Lom, Pribyl and Svitek, 2016), and provide solutions to some longstanding problems such as increasing logistics costs and economic inefficiencies (Havenga, 2015). Thus, the role of national-level policy can be seen to be instrumental in driving the emerging transformation. The end goal of the transformation would be connectedness of government, citizens and business, with a need for vast investments in telecommunications and internet infrastructure technologies such as broadband and internet connectivity to reduce the digital divide and provide digital connectivity for communication efficiency, collaboration and integration of citizens, business systems and government (Manda and Backhouse, 2017).

Developments in the international environment have been instrumental such as rising geopolitical volatility and competition between leading industrial companies in 5th Generation technology leadership (Ustundag and Cevikcan, 2018), global production networks and climate change mitigation (environmental modernisation) (Schwab and Samans, 2016). Other developments have been within regional economic relations and intra-societal transformations, such as rapid urbanization (Sanchez-Sepulveda, et al., 2019), information intensity and changing consumer behaviour (Harting, et al., 2019; Verhoef, et al., 2019), rising aspirations of women and gender dynamics in the workplace and across industries (Schwab and Samans, 2016), crowdsourcing and the sharing economy (Verhoef, et al., 2019) and distribution of company share value across digital firms on major markets (Jimenez, et al., 2018).

These forces in technology development with shifting value towards digitally modelled businesses, interconnectedness, social trends and international relations have shaped technological transformation that is irreversible yet uncertain in its outcomes given the social and economic structural disparities across national boundaries and within countries at different stages of economic development. Robotics, artificial intelligence and automation will displace low skilled, repetitive and routine jobs in the service industry, transport and energy sector, leading to job destruction (Kaivo-oja, et al., 2019; De-Ruyter, et al., 2019). Digital production networks for example enable entrepreneurs and businesses to access larger markets and increase their product coverage to a larger number of consumers. Digital technologies facilitate access to labour market information with companies being able to hire the most talented individuals heightening labour market competition. New jobs are created for these tasks with labour market benefits for those trained and participating in more competitive labour markets (Galindo-Martín, Castaño-Martínez and Méndez-Picazo, 2019).

The changing social relations of production and technology to human interaction will require new social relations of production and human welfare (De-Ruyter, et al., 2019). Finally, technology adoption will result in the restructuring of the skills profile of jobs, which will result in increased competition in typically male-dominated sectors, as skills requirements will shift from physical and brute strength or masculinity towards mental strength and soft skills (Webster and Ivanov, 2020; Schwab and Samans, 2016; Ulas, 2019; Manyika, et al., 2017). DT is thus viewed as providing tools to eliminate gender constructs and limitations leading to empowerment of women and contributing towards gender equality and strengthening the position of women in the labour market (Aly, 2020). Furthermore, DT is argued to make possible flexible arrangements for work, including remote work, and make it possible to combine paid work with non-paid labour which predominantly constituted women’s responsibilities, thus improving women's socioeconomic prospects.

Vast research that has been discussed has provided scope for gains and societal advancement along various fronts, however, the assumptions taken have been that the societies have institutions and structures that enable them to adapt to DT with minimum socioeconomic disruption in terms of human welfare. However, in this study, it is argued that the costs associated with DT in unequal societies, particularly those with negative initial conditions require other broader considerations than merely the possible gains and the prospects of a smart society, since the majority may be marginalised causing negative outcomes to the economy and society and heightening already existing inequities.

3.3.4. Impact of disruptive technological change on employment.

Disruptive technologies are normally preceded by the wide adoption of technology-induced transformation in the economic sphere before societies adopt the technologies. While this is true of the historical technological transformations, it is not true of the era of digital transformation. Changes in social structures have resulted in societies widely adopting digital technologies and beginning to adapt to their effects almost synchronistically with adoption in business and economic circles (Muhleisen, 2018). This means that the pace of disruptive change of DT is unprecedented, particularly where there is the existence of structural failures, such as poorly designed education systems (Spaull, 2013), poor performing and polarized labour markets and economy-wide digital skills shortages (Pineda, 2019).

Within this scope of expected change, some researchers predict dramatic change while others predict only marginal changes, with the bulk of the forecasts being placed on labour market participation, income and economic welfare (Nam, 2019). According to authors who propose dramatic change as the outcome of digital transformation, technologies such as artificial intelligence, robots and automation will displace jobs that are predominantly based on low-level human skills and of a routine nature, those not requiring high-end human skills, with changed job structure of remaining occupations (Brynjolfsson and McAfee, 2014; Arntz, Gregory and Zierahn, 2017; Frey and Osborne, 2017).

DT results in change not only of jobs and skills composition, but there is also expected job destruction in estimated millions of jobs (Afonasova, et al., 2019), and massive overhauling of industries expected in industries that can easily automate in manufacturing and service industries (Schwab and Samans, 2016). While not all aspects of jobs can be automated at least in the short to middle term, polarization between high skilled jobs, requiring high-end soft skills—cognitive skills, decision making, social skills—and low-level skills—non-automatable aspects of physical works in construction, manufacturing and food production and processing. This polarization will result in a pronounced widening of income inequalities (Afonasova, et al., 2019). The impact of the coronavirus crisis has forced companies in various consumer sectors to shift towards online commerce platforms in retail, banking and food merchandising accompanied by retrenchments and job losses, indicating the premonitions of a highly transformed socioeconomic structure when the pandemic assuages globally, with a more distinct irreversible phase of DT (Stock, 2020). Global production restructuring will be accompanied by a massive change in economic restructuring caused by the adoption of intelligent technologies, advanced computing, connectivity and big data with disruptive outcomes (Okhrimenko, et al., 2019). Costs of internet connectivity, technological and transport logistics will be instrumental in deciding global distribution of economic activity, with restructuring in the global concentration of talent and skills, and within society polarization (Balsmeier and Woerter, 2019).

Empirical research has shown that since the middle of the second decade of the 21st century, economic organizations undergoing either digitalization or DT of their production relations, have seen workforce reduction and gains in production efficiency (Katz, 2017). While these changes have occurred in the developed world, these documented experiences reveal the stark challenges in the pace of technological transformation in the developing world associated with DT (Katz, 2017). Work sustains society and provides for the material needs through which human beings develop as social beings irrespective of the area of work. A displacement of this important aspect of work can restructure society in ways that are novel and socially disruptive (Ryder, 2018).

The changes in the temporal and spatial organisation of work are important outcomes of digital transformation. For instance, technological innovation enables more precise monitoring of economic activity and allow for a dispersed system of production and exchange to be integrated. Since advanced countries are leading the development of technologies driving digital transformation, the concentration of high-end skills will be in those countries, creating global disequilibrium in the global division of labour (Ryder, 2018). High-end skilled aspects of production and exchange will likely be controlled by these countries, while low-end aspects will be outsourced to developing and emerging countries. The same effects are also reproduced in local economies to some extent creating challenges such as loss of opportunities, social marginalisation, loss of employment and welfare loss (Ryder, 2018). Losses in employment, social exclusion and unequal redistribution of income are associated with digital transformation.

3.3.5. DT and socioeconomic effects

As discussed in the foregoing sections, the effects of DT on the economy and society depend on the capacity of the underlying socioeconomic structure to adapt and adjust to the developing transformation in the society. Structures of society cannot be assumed to remain constant when future technological transformations, global integration and demographic change occur influencing changes in the mode of social and economic production and exchange (Kaivo-Oja, Roth and Westerlund, 2017). Some scenarios that have been presented in debates have focused on the dividends of demographic change. In countries with ageing populations shortages of qualified labour have been seen to likely arise due to the retirement of large cohorts of workers with population ageing likely to lead to pervasive reallocations of labour and resources across sectors and occupations as consumer preferences change, shifting consumption patterns towards the demand for services (healthcare). This means a sectoral change in the demand for labour, with higher-end skills being more likely to be absorbed than low-end skills, which places the challenge on whether the existing relations of production and reproduction can meet the skills demands of the new socio-economic arrangements (Kaivo-Oja, Roth and Westerlund, 2017).

This scenario can also be seen to result in competition for high-end skills between developing, emerging and developed countries, which can result in the former not benefiting from demographic dividends or investments in human capital development. Developed countries are better able to attract and retain talented human capital than developing countries since they can offer better incentives in terms of remuneration and talent development. This means that there is a high likelihood of high-end talent being concentrated in advanced economies even when such talent has been developed through investments made in developing countries (World Economic Forum, 2016). At the local level, the urban-rural divide will mean that urban areas will attract more skills and advancement, entrenching developmental challenges and backlogs in the rural areas. In countries with a young and growing workforce such as South Africa, outmigration will most likely result in skills losses, thus shifting returns to human capital development towards more advanced industrial countries (OECD, 2017). To benefit from the demographic dividend in South Africa, there is a need to ensure that the young demography making the future labour force has the requisite competencies and skills necessary to effectively participate in the transformed society. The expectation is that DT will likely entrench the polarizing occupational structure into high skilled-high paying jobs on one extreme and low skilled-low paying employment on the other (OECD, 2017).

In another study by the World Bank, it was demonstrated that the speed of polarisation will depend to a large extent on the speed with which new technologies are adopted (Maloney and Molina, 2016). In the present era, the Covid-19 crisis has accelerated the pace of technological adoption in the home, consumer industry and the workplace in South Africa with the polarisation of the labour market, and massive increases in unemployment (Mhlanga and Moloi, 2020; Datta and Nwankpa, 2021; Posel, Oyenubi and Kollamparambil, 2021). The polarisation of the labour market has also presented the reality of the digital divide in South Africa concerning empowerment. This divide can be viewed from the capabilities perspective as referring to the use of digital technologies, thus focusing on those who have the skills to use digital technologies productively and remain relevant to a transforming economic system as opposed to those who do not have those skills, who have experienced job loss and welfare loss (Coeckelbergh, 2011; Datta and Nwankpa, 2021). This demonstrates the assumption that as the

General-Purpose Technological platform of the society changes, patterns of social interaction in the relations of production and exchange change, with changes in social and cultural relations of work and redistribution of economic welfare (Maloney and Molina, 2016).

If polarisation and socioeconomic exclusion can be experienced at the pace it has been demonstrated in South Africa through analysis of the labour market loss in employment (Dengler and Matthes, 2018), then DT has more pervasive redistribution effects across the socioeconomic system as its integration deepens to extended functions of life, business and society (Kadar, Moise and Colomba, 2014). Business operations since the opening of the second decade of the 21st century is inconceivable without the internet and its various tools to manage operations and maintain competitiveness and productivity, which means that the future is characterised by heightened demand for digital technology linked skills (Kadar, Moise and Colomba, 2014).

3.4. Mitigating Digital Transformation

Throughout history, the technological transformation has been met with social and political resistance mostly by those who expect to lose from it. In the inevitable DT era, technological unemployment is the pervasive and impending mounting problem that will bring with it greater inequalities in income, economic opportunities and social privileges and an increasing gap between labour share of income versus capital share of income (Peters and Jandric, 2019). Thus, those with advanced capital formations both physical and human will likely experience welfare gains, while deterioration of welfare might be the consequences at a greater scale for the less capital endowed, thereby exacerbating the initial inequalities and inequities characteristic of South Africa. In this section, an in-depth analysis of the factors discussed in the extant literature will not be attempted, yet the pressing issues are presented in sub-section 3.6.1 below.

3.4.1. Considerations

DT is policy-driven, whether it is an industrial policy directed at an industrial sector or national innovation policies. Through policies, the government develops social, economic, industrial and labour market policies that are responsive and can better prepare businesses, society and government to leverage the opportunities and address the challenges of DT (Manda and Backhouse, 2017). It is policy innovation that plays the central role in addressing skills, education, infrastructure and other needs arising from innovations. Thus, considerations of the design of policy, its implementation and the forces that shape policy design will be important considerations in understanding how DT will restructure South African society and change the welfare opportunities for citizens. Consider industrial policy, for example, if DT processes enhance market access, then job growth will be experienced in that sector. However, if DT primarily drives efficiency growth maybe through replacing capital for labour, then job losses will be likely (El-Darwiche *et al.*, 2013).

Classical economists agree that DT will bring about massive losses in employment and income, yet despite these losses, the economic theory points out the existence of indirect effects argued to counterbalance the losses in employment-related welfare. According to these economists, technological changes produce various market compensation mechanisms, new machines, improved productivity and lower prices, new investments and lower wages which can offset the influence of labour-saving innovation (Piva and Vivarelli, 2004; Vivarelli, 2014). This understanding seems to be the dominant reasoning informing policies driving digital transformation. However, earlier studies have indicated that access to technological systems and training skills are important to how well the benefits of technology can be realised (Matuzeviciute, Butkus and Karaliute, 2017). Growth of income inequality and the digital divide can influence people's motivations, access to innovation networks and skills in sharply non-converging ways. Rural and urban differences can be large and potentially exacerbated by DT and also by policies shaping it. Regulation can also change the future direction of digital transformation. There is thus a need for institutional formations that while driving digital transformation, will also take into consideration the structural imbalances and differences among geographies, with the role of regulation shaping the direction of digital transformation.

The emerging transformation has been accompanied by the rise of what is termed the platform economy. The importance of this economy has been that it has accorded employers access to a much larger pool of specialised labour and skills at a fraction of the costs of hiring using traditional contracts (OECD, 2017). Through platforms, workers have the flexibility to arrange their work according to their needs since they can choose where and when they work, which can greatly expand working opportunities for parents, students and other groups. Platforms thus enable workers to have multiple job tasks, undertake long working schedules and are usually under high stress, since their remuneration is task-related and depend on highly specialised labour work. Since the work is not based on traditional contracts, there is no social security, which is highly risky with low wage rates due to high competition since the labour market is unregulated spanning the entire spectrum of the global labour force (OECD, 2017). Since the platform is not regulated, it has created many work opportunities for workers in emerging economies while also engendering a race to the bottom in remuneration and working conditions, with the bulk of the work undeclared and informal. Thus, pervasive platforms can foster the development of educational systems that enable specialisation in various IT related fields. While regulation such as corporate social responsibility provides for in-house training and development under traditional contracts, the platforms require that workers meet their developmental needs by themselves. Those with access to income and training opportunities advance better than those without meaning that imbalances in initial skills endowments in the population are exacerbated and inequalities aggravated (OECD, 2017). Non-standard forms of employment have been associated with lower job quality, lower wages, fewer employment-related benefits, increased job insecurity and high job strain. The workers may receive less training, lower career advancement opportunities than workers under traditional contracts and where platforms are pervasive, they will likely foster skills imbalances and contribute to structural skills paradoxes presently constraining economies across the globe.

In another paper, a researcher argued that technological change would deskill the workforce since technological advancement serves to automate production processes that previously required complex mechanical knowledge and human activated procedures. The highly IT integrated nature of work in the gig economy or on the platform economy is tech-influenced and reduces the need for the human agency as routines can be automated through intelligent machines and optimized. Thus, rather than empowering independent workers, platforms and gig work can serve to reinforce the commodification of labour and undermine existing labour arrangements (Cherry and Aloisi, 2017). Furthermore, applications enable increased surveillance over task performance, which increases labour commodification. According to Stewart and Stanford, (2017), the onward progression of technology is neither neutral nor exogenous and the kinds of technologies that are developed and implemented and their effects on work, production and social exchange are reflective of the interests of competing constituencies. The arguments for DT have to do with the benefits of decentralisation and disintermediation, giving people more control over their work and social lives, however, platforms can be seen to re-intermediate the working relationship between firms and workers while also blurring the distinction between paid and unpaid work. Under traditional contracts, individuals are remunerated for their skills and talent, however, in the platform economy, critical mass platform providers such as Facebook and LinkedIn derive financial benefits from the co-creation of content from users who are not paid workers (De Ruyter, Brown and Burgess, 2018). Power dynamics between these firms and employees are evident in the skewed nature of bargaining processes, such that decentralised workers cannot collectively bargain for better terms nor do they have power enough to determine terms of relationship with these giant platforms. Thus, the DT economy has deeply entrenched political issues, particularly concerning the welfare of workers and employees in the new economy.

Finally, remote working arrangements means that work will be located from designated areas, with an increase in work involving interaction with ICTs. Given this dispersion of work, political and regulatory challenges will set in, since as work becomes invisible and geographically dispersed through platforms and online work arrangements, governments will have challenges regulating employment, identifying employers, engaging in tax collection and supporting protection through pensions (De Ruyter, Brown and Burgess, 2018). In the traditional economy, with regulated contracts, unions and bargaining processes, gig work could be seen as a new variation of putting out, subcontracting with no employment security and unpredictable employment patterns and consequently income. In such settings, gig work made-up forms of contingent and informal work with ambiguous employment statuses and eroded employment conditions, which in the digitally transformed economy, become mainstream work arrangements, with deeper issues for socio-economic welfare.

3.5. Chapter Summary

DT impacts the technological framework of society on which economic activity is built changing social institutions and relations of production and exchange. This transformation driven by advanced technologies and envisioned goals of planetary sustainability has both positive and negative effects influenced prominently by the socio-economic conditions of societies experiencing technological transformation. DT is different from previous waves of technological transformation in the absence of lags between technology development and its implementation in society resulting in its effects being experienced without societies having adjusted both institutionally and at a policy level. These are issues that need to be considered in developing interventions rooted in a broader understanding of the effects of DT on socioeconomic issues. The need to understand socio-economic issues at the micro-level and integrate this knowledge with an understanding of DT is the argument for the positionality of this present research study.

Chapter 4: Research Methodology

4.1. Introduction

This study employed a secondary analysis of the National Income Dynamics Study (NIDS) waves 1-5 data sets and the World Economic Forum (WEF) DT focused group discussions on finding pathways to socially and economically beneficial DT in South Africa. This chapter outlines the research philosophy of pragmatism and its implementation in this study, the sequential explanatory research design, the datasets, data analysis and establishing validity and reliability in the study.

4.2. Research philosophy

4.2.1. Pragmatism

Research philosophy refers to the set of assumptions about the world and the frame of thinking informing a worldview (Creswell and Creswell, 2017). As a research paradigm in this study, pragmatism is based on the premise that researchers can bring into their research work the philosophical or methodological approach(es) that works best for the particular research problem being investigated (Kaushik and Walsh, 2019). As an approach to the construction of knowledge, pragmatism concerns itself with the application of knowledge to find a solution(s) to the research problem (Creswell and Creswell, 2017). Pragmatism is thought of as a practical philosophy in which truth is not viewed as absolute but a moveable and usable construct for understanding the nature of reality. Thus, pragmatism is concerned with the operationalisation of theory in practical situations or the application of theory to practice. Pragmatism also argues that the world is not static but in a constant state of evolving or becoming, through human instrumentality with human experiences and actions being pivotal to pragmatism (Kaushik and Walsh, 2019).

Actions according to pragmatists are situation and context-specific with the situations and contexts in which those actions are taken being important considerations. Pragmatism adopts the premise that there is no consequential dichotomy between the objective and the subjective world since what is considered objective has a grounded subjective reality within which it is framed (Given, 2008: 673). This positions pragmatic philosophy with the premise of the socially constructed nature of knowledge and reality through habits, beliefs and decisions that underlie human experiences. According to pragmatists, knowledge claims cannot be completely abstracted from contingent beliefs, habits and experiences of those developing the knowledge (Kaushik and Walsh, 2019).

4.2.2. Implementing pragmatism in the research study

Following from the argument established above that in adopting pragmatism, researchers adopt the philosophical and/or methodological approach that fits best the particular research problem being investigated. To this end, pragmatism provides the milieu for mixed-method research as its assumptions provide the essence for mixing methods in research. Pragmatism is an advanced philosophy providing the epistemology and logic for combining quantitative and qualitative approaches and methods. It permits the mixing of paradigms, assumptions, approaches and methods for data collection and analysis (Creswell and Creswell, 2017; Maarouf, 2019).

In this research study, pragmatism is adapted for providing the basis for the integration of quantitative and qualitative methodologies in the collection and analysis of data to arrive at the conclusions of the research. As pragmatism is oriented towards solving practical research problems in the real world, it allowed for bringing together methodologies that can help in bringing together two streams of data in building an explanatory framework for addressing the emerging issue of digital transformation. Functional pragmatism argues for knowledge directed at designing actions or interventions, which derives from a multidisciplinary approach to knowledge creation, which is the core argument for employing mixed methods in this study since there is no single dataset either quantitative or qualitative that could provide the analysis required to address the issues of inquiry in this study, pragmatism provided the basis for such an approach hence leading to knowledge creation for decision making. Referential pragmatism or knowledge about action implies pragmatism describes the world in an action-oriented way, quantitative analysis in this study provides the dynamics of the individuals experiencing digital transformation while qualitative analysis provides an understanding of the nature and processes of digital transformation hence combining real experiences and knowledge in developing interventions (Given, 2008; Creswell and Creswell, 2017; Maarouf, 2019).

In implementing pragmatism philosophy, two methodologies are adopted within a mixed-methods premise, the post-positivist approach and its emphasis on observation and measurement, and the critical theory method which emphasizes the need to critically assess the existing state of affairs as a precursor to the attainment of the desired state (Given, 2008: 175). These approaches to knowledge construction integrated within a functional and referential pragmatic approach are explained below.

4.2.2.1. Post-Positivism approach

Post-positivism emerged as a result of the critiques of the positivism philosophy and its emphasis on the objective nature of reality and the ability of science and measurement to observe that reality (Given, 2008). Positivism essentially emphasizes the importance of observation for the growth of knowledge and employs the measurement of phenomena as central to the development of understanding. The philosophy furthermore requires the existence of a theoretical framework within which to structure data. Data according to postpositivists is central in measuring and testing the tenets of a theory. The adoption of postpositivism in this research study centres around the innovation of the philosophy as opposed to positivism (Given, 2008; Leavy, 2014). While positivism focused on knowledge observation using empirical observation, to create generalisable theories, postpositivism accepts context-based empirical observation and allows for non-observable sources of data, such as those derived from human experiences, reasoning or interpretation. Postpositivism accepts the importance of settings and context as vital to social science research and argues that claims to knowledge require complete contextualisation.

4.2.2.2. Critical Theory approach

Critical theory can be explained as a foundational perspective from which an analysis of social issues, politics and human behaviour, science and other behavioural approaches can proceed. Research, based on critical theory, begins with a critical assessment of the existing state and utilises this to develop the requirements to reach the desired state. In applying critical theory, the focus is placed on dialectic reason, the discourse of ideas between parties holding perspectives about a given subject as a means to study the conditions under which people subsist (Given, 2008: 176, 177). The historical analysis becomes central to critical theory through interpretive analysis of human experience through existing data on historical actions and decisions. The historical analysis makes use of documentation as sources of data, with documents providing information on policies of technological transformation, transport, energy, economy and so forth. Other research documents connected to historical analysis can be notes on debates around policy proposals or anticipated changes in social exchange (Leavy, 2014). Such evidence forms the basis of critique, with the critical theorist interpreting the evidence in terms of its effects on those individuals and segments of the society that have the least influence on the designed policies. Individuals thus become the key centre of analysis who are affected by events brought about by human actions (Given, 2008). There is a need to address the challenges of the existing social reality, identify actors and agencies for change, provide a clear normative basis for criticism and identify practical goals for social transformation.

4.3. Research Design: Explanatory sequential mixed methods design

The research design refers to the general plan or strategy for conducting a research study to examine specific testable research questions (Lavrakas, 2008). The research design essentially outlines the nature of the research questions and hypotheses/propositions, the variables or measurements involved, the sample of participants, the data, and the data analysis methods. This study adopted a mixed-methods strategy using quantitative and qualitative data to meet the objectives of the study and address the research question of the study. In this mixed-methods design, the study adopts both a deductive approach using quantitative analysis and an inductive approach on qualitative data analysis, with the use of statistical analysis and inductive thematic analysis respectively (Andrew and Halcomb, 2009).

In this study, the quantitative nested sequential explanatory mixed methods design is employed. In a quantitative nested sequential mixed methods study, quantitative data forms the foundational analysis from which explanations are sought for the quantitative findings through sequential collection and analysis of qualitative data. The sequential explanatory design is characterized by an initial quantitative phase which is followed by qualitative data collection and analysis. Findings from the qualitative study component are used to explain and contextualize the results of the analysis of the quantitative study component. The results of the quantitative analysis are essential in designing and directing the collection of qualitative data with the integration of results in the interpretive phase of the research (Andrew and Halcomb, 2009). This design is well suited in studies in which a researcher/researchers require qualitative data to explain significant (or non-significant) results or to place quantitative analysis results in context. The quantitative nested sequential explanatory mixed-methods study provided an orderly model for implementing the pragmatic approach to employing mixed methods in addressing the research inquiry. By bringing together the dynamics of individuals and the new arrangements in transformed socioeconomic arrangements under digital transformation, the researcher can address the broader questions of socioeconomic welfare changes under digital transformation in South Africa. Furthermore, since digital transformation is an emerging research area (Verhoef *et al.*, 2021), contextualizing the development of concepts of digital transformation and testing such concepts in how they explain empirical findings is instrumental in operationalizing the use of such concepts in understanding the emerging field. As such the explanatory sequential mixed methods design meets the functional approach to knowledge development undergirding the pragmatism approach to knowledge development (Maarouf, 2019).

4.5. Data

4.5.1. The National Income Dynamics Study

The National Income Dynamics Study (NIDS) dataset is obtained from SALDRU, Datafirst under a public use license from the University of Cape Town (Appendix 3). It is a longitudinal panel dataset, currently composed of 5 waves commencing with wave 1 based on surveys conducted in 2008 and ending with surveys conducted between 2016-2017 making up the 5th wave of the dataset. The dataset is the outcome of the vision of the South African presidency in efforts directed at undertaking a continuous assessment of the changes in the well-being of South African individuals and households through following closely a nationally representative sample of 28000 individuals and 7305 households (Woolard, Leibbrandt and Villiers, 2010; Branson and Leibbrandt, 2013; Leibbrandt and Woolard, 2016; Brophy *et al.*, 2018). The target population in the NIDS dataset is individuals in private households in all nine provinces of South Africa and all residents in worker accommodation such as hostels, convents and monasteries (Brophy *et al.*, 2018).

4.5.2. Digital transformation qualitative data

The DT dataset is based on the 2016 to 2019 conferences of the World Economic Forum Digital Transformation Initiative (DTI), whose main objective was to offer unique insights into the effects of digital technologies on business and the wider society in the coming decades. Since digital transformation is perceived as a novel phenomenon whose wider effects are not completely understood, the WEF partnering with other organisations, businesses, industry, world leaders and academics, engaged in discussions concerning the various ways in which, digital technologies would affect the world economies and societies. This was the case, particularly concerning social and economic aspects such as human capital, education and skills, income distribution, platforms, internet technologies, and social infrastructures. These discussions focused on what constitutes the general technology platform undergirding the arrangements of production and exchange within any economy projected to create transformed social and economic arrangements of production and exchange.

4.5.2.1. Target population

The target population included all participants at the WEF conferences, such as academics, entrepreneurs, business executives, world leaders, industry experts, technology developers and others who were participants in focused group discussions in any of the topics that met the criteria explained in section 4.5.2.2 below.

4.5.2.2. Selection criteria

In this study, the assumption was made that participants are specialists within limited disciplines limiting their understanding of DT and its processes to their specific area of focus. This implied that a single focused presentation or one-on-one interview will not likely provide diverse insights since the study required a multidisciplinary engagement. With this consideration, all focus group discussion sessions on issues including employment and income, jobs strategy, drivers of digital transformation, social contracts and skills in the fourth industrial revolution were selected in line with the theoretical premises presented in Chapter 2. These forum discussions, which were accessed in video format were downloaded, transcribed into text and compiled into the corpus of documents used as the qualitative dataset in this research study. The focus group discussions from the conference are publicly available on the World Economic Forum website on digital transformation, under a creative commons license, which allows for the reuse of the materials.

4.5.2.3. Qualitative Data Sample Size

A total of 20 focused group discussions were selected and comprise the qualitative data corpus of transcribed video files of the focused group discussion with each focused group discussion having a length of at least 40 minutes, which was enough time for engagement providing a rich qualitative dataset.

While the thematic analysis was directed at developing concepts and substantive theories, these were directed at explaining the pattern of results in the quantitative analysis. There was no directed development of new theories hence the choice of the sample size was not directed by the need for theoretical saturation necessary in grounded theory research studies *see* (Thomas, 2006). Furthermore, there was no attempt made for an exhaustive qualitative analysis of digital transformation for standalone qualitative theory development, the small sample was considered adequate.

4.6. Data Analysis.

4.6.1. Quantitative data preparation and management

To eliminate errors in data preparation, a concise reading of the technical information presented with each wave of the data was undertaken, with focus placed on common variables, weights, sampling design and the treatment of missing information on variables. Such documentation was also used in the selection of variables that have been used in the analysis that has been undertaken, with the preparation of such variables and their transformation explained in section 4.6.2 below.

Multiple imputation method was used for the handling of missing values; however, it was undertaken at the primary data preparation stage, which accounted for all missing values within the dataset for variables with missing information less than 30% of the observations of a given variable (SALDRU, 2013; Leibbrandt and Woolard, 2016). All other variables with missing information were incorporated into the analysis without adjustment, using case wise deletion as necessary as Stata (Statistical Analysis Software) analytical procedures in both descriptive and inferential statistical analysis exclude missing information in computation using case wise deletion. Given the robust statistics that were obtained, the treatment of such missing information was found to be adequate.

4.6.2. Quantitative analysis variables

In undertaking supervised analysis of the quantitative data, continuous indexed variables were created using principal components analysis, a method for data reduction and useful for coalescing correlated or uncorrelated variables into a composite of latent attributes of the variables (Vyas and Kumaranayake, 2006). Using PCA, six composite variables were created which are the digital index, the socioeconomic index, the social exclusion index, the human capital index, the upskilling index and the job competencies index which were composed of sub-indexes. In the descriptive analysis of the continuous variables, the changes in the statistical mean and its distribution were the chosen parameter. In inferential analysis, the multiple linear regression model was used to track the influence of socioeconomic and other variables on the metrics measuring the digital status of individuals. In creating these indexed variables, no attempt was made to reduce the variables to a singular index by taking the component with the highest eigenvalues as in other studies (Vyas and Kumaranayake, 2006; Howe, Hargreaves and Huttly, 2008; Earnest *et al.*, 2015). The various components with eigenvalues above the threshold of one (1) were used in the creation of sub-indexes for each umbrella index variable so that all the dimensions of each variable were exhaustively captured in the analysis. These were the principal variables that were used in both the descriptive and inferential analysis presented in Chapter 5.

4.6.3. Qualitative data preparation and analysis.

4.6.3.1. Inductive and deductive thematic analysis.

Thematic analysis is a data reduction method applied in the analysis of qualitative data. It refers to a search for themes emerging from the data as being important to the description and understanding of a phenomenon (Fereday and Muir-Cochrane, 2006). The data reduction process involves the identification of themes through careful reading and re-reading of the data. It can also be understood as a form of pattern recognition within the data where emerging themes become the categories for analysis (Fereday and Muir-Cochrane, 2006). In this study, the approach adopted in the thematic analysis is the data-driven inductive approach developed by Boyatzis (1998), in which the coding process involves recognizing important moments in the data and encoding them before the process of interpretation (Boyatzis, 1998). In addition to this approach, the study also adopted the template or apriori coding approach, in which the researcher created a template before commencing an in-depth analysis of the data. The template of apriori codes was developed from research questions and the theoretical framework (Chapter 2) (Waring and Wainwright, 2008). Using these approaches to thematic analysis in this study means that research questions were made integral in the process of deductive thematic analysis while allowing for themes to emerge from the data reduction process using inductive coding. In using the deductive thematic analysis approach, a template was created from the research questions and the theoretical framework and applied as a primary means for organizing text for subsequent interpretation. This template effectively directed the phenomenon to look for during the inductive in-depth analysis of the data.

The template thus works effectively as the evaluative tool since it directs the focus of the analysis by defining domains and topics to be investigated. While the findings are influenced by the evaluation objectives outlined in the template, the findings arise directly from the analysis of the raw data, not from prior models. The template provides a focus domain of relevance for conducting analysis and not the set of expectations concerning specific findings of the analysis (Boyatzis, 1998; Thomas, 2006). The analytical strategy adopted in this research study was the use and application of template analysis to rich, unstructured qualitative data following the primary data collection phase, to ensure that unstructured data is broadly categorized at a semantic level of thematic analysis in preparation for inductive thematic analysis of the categorized data, enabling analysis within a defined analytical template or framework.

4.6.3.2. Conducting thematic analysis in the study

Following the preparation of data from 20 transcripts of the focused group, the edited and cleaned transcripts were entered into the QSR NVivo 12 qualitative data analysis and management software. A comprehensive process of data coding and thematic identification was then conducted systematically. The deductive thematic analysis template was generated and immediately utilized in the initial coding of the data without pretesting its reliability with the justification that it was developed from the extant literature and central questions of the research as shown in the table below. A generalized approach to initial code generation was undertaken to allow for initial broader coding and directing the nature of data to extract from the qualitative data during the second stage inductive and in-depth coding process. This approach was also deemed practical and effective since the goal was to find an explanation by focusing on specific information and themes from the qualitative data. The apriori template is presented in Table 3 below.

Table 3: Template of Priori codes.

Literature driven codes	Description of Code
Socioeconomic effect	General-purpose technologies restructure the social and economic arrangements of production and exchange thus resulting in socioeconomic outcomes (Okhrimenko *et al.*, 2019).
Skills requirements	Theory Driven: New arrangements of economic activity creates a demand for new skills with each change in technology bringing with it its skills demand matrices (Rodrigues, 2017).
Adaptation	Theory driven: Changes in the arrangement of social and economic structures requires complementary policies, training, institutions and preparedness among those experiencing the change (World Economic Forum, 2016; Kaivo-Oja, Roth and Westerlund, 2017; Ryder, 2018)
New social contract	Theory driven: In the age of digital transformation, the use of platforms, and remote work which does not conform to existing regulation of working arrangements, has the potential to erode employment tenure and security negatively affecting societies, hence the need for new social contracts (OECD, 2017).
Research question-driven code	

Digital transformation	Focuses on the processes of DT and how these will shape the economy and society.
Opportunities	What are the opportunities of digital transformation?
Challenges	What are the challenges of digital transformation?
Institutions	Role of the labour market and other social institutions such as education and training institutions in shaping adaptation to DT (Branson and Leibbrandt, 2013).
Labour market participation	The labour market is the central social institution in the redistribution of income and hence the socio-economic welfare of individuals and households.

Table 4: Implementation of the coding manual in NVivo.

Nodes

Name	Files	References	Created On
Adaptation or Mitigating DX	5	16	7/12/2021 2:54 AM
Creating opportunities	4	12	7/13/2021 1:36 AM
Digital asset investment and connectivity	1	2	7/13/2021 6:37 PM
Educational Reform	4	18	7/13/2021 6:33 PM
Inclusion in technology development	2	4	7/22/2021 8:56 PM
Challenges of digital transformation	2	5	7/12/2021 1:38 PM
Digital transformation	4	36	7/12/2021 1:36 PM
Institutions	5	9	7/12/2021 1:39 PM
Labour market participation	4	11	7/12/2021 1:41 PM
New Social Contract	1	16	7/12/2021 1:35 PM
Opportunities of DX	8	21	7/12/2021 1:37 PM
Platforms and Employment	4	42	7/13/2021 1:09 AM
Political Issues	1	3	7/15/2021 12:51 AM
Skills and Competences	6	29	7/12/2021 2:52 AM
Socioeconomic effect	3	11	7/12/2021 2:50 AM
Current arrangement have negative outcomes	2	4	7/13/2021 7:01 PM
Digital Divide and Access Imbalances	3	7	7/15/2021 12:28 AM
DX can fuel monopolies	2	2	7/13/2021 7:06 PM
Income distribution under DX	4	21	7/13/2021 12:26 PM
Spatial influences	2	3	7/13/2021 8:11 PM
Technology governance	5	25	7/13/2021 9:19 PM

Source: Extract from NVivo manual coding.

4.6.3.3. Summarizing data and identifying initial themes

In summarizing each piece of textual data from the transcripts, the process commenced with reading and comparing the recorded transcripts of the data with the video recordings from which the transcripts were made, so that text could be matched and the levels of interaction in which ideas were exchanged recorded.

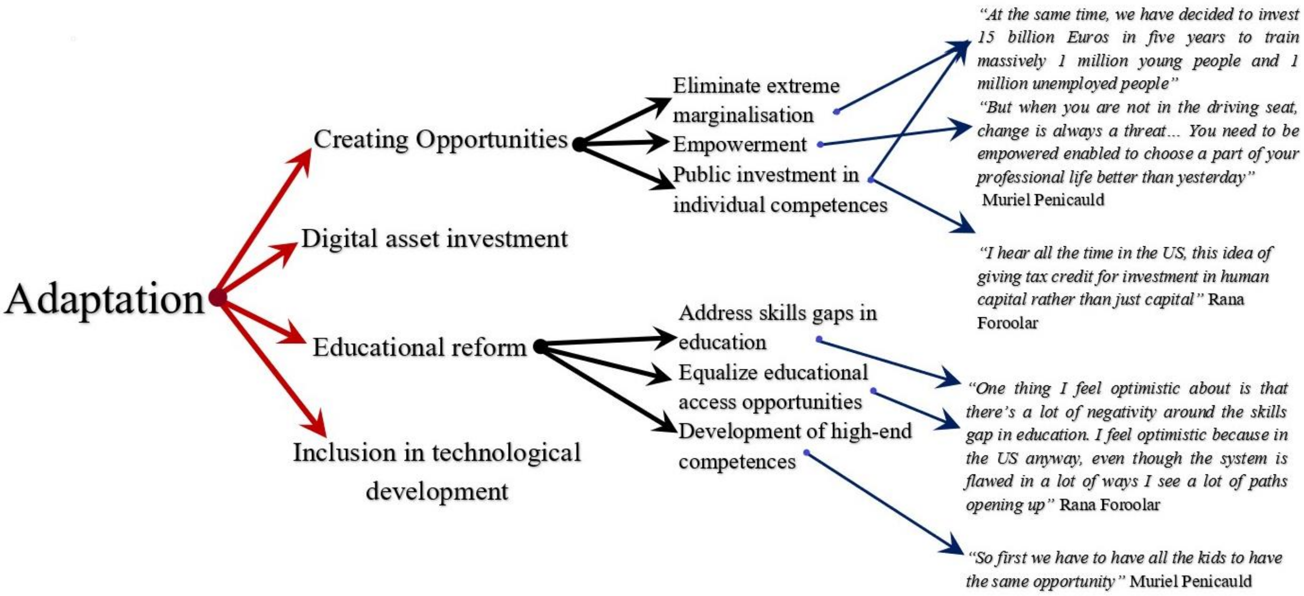
The coding template was applied to the text with the intent of identifying meaningful units of text and extracting text into broader semantic themes so that focus was directed on broader themes relevant to the context of the study. By limiting the in-depth analysis to specific areas of the raw text, as determined by the template, an in-depth analysis could be conducted more meaningfully on the aspects of the data aligned with the goals of the research study. During latent analysis of transcripts, inductive codes were assigned to segments of raw text that described a new theme observed in the text. These inductive codes were either separate from the initially predetermined codes or expanded the initial codes and presented broader/latent aspects of the initial codes from the template.

4.6.3.4. Aggregating codes and identifying themes

The discovery of themes and patterns in the data required that codes be aggregated and linked together. During this stage of data analysis, codes having commonalities are aggregated together and linked to a larger grouping or theme. Since codes capture the meaning of the phrase of text extracted and are used in indexing the data and grouping together phrases with similar ideas or meanings, a theme becomes a higher-level aggregation of these meanings and ideas (Chapman, Hadfield and Chapman, 2015). This stage of the analysis carries a high degree of subjectivity requiring the researcher to demonstrate methodological validity by minimizing bias through careful notes demonstrating justification regarding selection or rejection of particular phrases, comparison and discussion (Chapman, Hadfield and Chapman, 2015).

To assess the robustness of the themes generated, the first 10 transcripts were completely analysed, the resulting themes were subsequently checked against raw data from the remaining transcripts. This was to assess whether the existing themes were robust or whether there could be new themes developing from the analysis of new raw data. In reviewing studies where data saturation was part of the methodological premises of the study, some researchers concluded that a minimum of ten interviews should be conducted and analysed followed by three consecutive interviews until there is no new themes emerge, that is repetitiveness becomes noticeable in the coding of the new raw data (Francis *et al.*, 2010).

Figure 1: An example of coding and thematic aggregation



Source: Own construction from WEF Qualitative Data.

4.6.3.5. Thematic legitimation and corroborating the findings

Corroborating the themes constituted the final stage of the thematic analysis as conducted in this study, which is the process of confirming the legitimacy of the findings. The previous stages were closely scrutinized to ensure that the aggregated themes were representative of the initial data analysis and assigned codes (Fereday and Muir-Cochrane, 2006). The interaction of raw textual data, generated codes and aggregated themes in this study involved several iterations before the analysis was extended to the interpretive phase in which units were linked into an explanatory model consistent with the text. In this phase, the devised themes were given legitimacy and refinement, in which the coded data extracts composing each theme were reconsidered to determine whether the themes formed a coherent pattern (Braun and Clarke, 2006; Fereday and Muir-Cochrane, 2006). The validity of the individual themes was considered to determine whether the themes accurately reflected the meanings evident in the raw textual data as a whole. In this stage, relevant issues not covered by existing codes were inserted where necessary, while used codes, where they substantially overlapped with other codes were deleted. Some themes were collapsed into other themes, while others were further disaggregated to give more insight into the analysis and the results. The final themes which were selected were specific enough to be discrete and broad enough to capture a set of ideas contained in several text segments. This was all undertaken to ensure that the data within themes cohered together meaningfully with a clear and identifiable distinction between themes.

4.6.4. Quantitative data analysis

4.6.3.1. Descriptive Statistical Analysis

Variables measuring social exclusion, socioeconomic status, digital asset index, human capital index, and job competency index were assessed across gender, spatial geography and population group. The findings from the analysis are presented in graphic plots and statistical tables, tracking marginal changes in the mean statistic of each index. The analysis was conducted across population groupings with the African population group being the reference category for comparison purposes. In the descriptive analysis, all the variables were assessed across the population groupings, with tabulations of population groupings against socioeconomic status, social exclusion, digital index, human capital index, job competency index and the upskilling index. The descriptive analysis presented in Chapter 5 tracks the changes in the mean of each index across the waves of the NIDS data.

4.6.2. Inferential Analysis

In performing inferential analysis, there was a need to account for sampling design to ensure that parametric estimates are computed with a robust variance-covariance matrix of the estimators (VCE). The multiple linear regression (MLR) model was used in running an inferential analytical model testing the influence of feature variables on the digital index as constructed in this study (section 4.6.2.3). Using survey design in regression modelling ensured that the sampling design of the data was taken into consideration in computing the parametric estimates.

4.6.2.1. The MLR Model

The multiple linear regression model takes the form

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{23} X_{23} + \cdots + B_N X_N + \varepsilon_i$$

And using the variables of the research study

$$\begin{aligned} \boldsymbol{DigIndex_i} = \boldsymbol{\beta_0} + \boldsymbol{\beta.\ SocioeconIndex_i} + \boldsymbol{\beta.Jobcompindex} \\ + \boldsymbol{\beta.skillsindex_i} + \boldsymbol{\varepsilon} \end{aligned}$$

The digital index is composed of separate variables which are used in the multiple regression, in turn, the feature variables on the RHS are umbrella variables with sub-indexes under them which are not presented in the equation for purposes of simplifying the presentation of the MLR model. The error term $\boldsymbol{\varepsilon}$ captures variation in the response variable, digital index not captured by the feature variables in the model. The multiple regression model to be valid required that the underlying data meet the following assumptions:

i. The dependent variable must be measured at the continuous level.
ii. There must be two or more independent or feature variables measured at the continuous or categorical level.
iii. There needs to be a linear relationship between the dependent variable and each of the feature variables and the dependent variable and all the features collectively.
iv. There must be independence of observations or independence of residuals which can be checked using the Durbin-Watson statistic.
v. The data must demonstrate homoscedasticity, in which variances along the line of best fit remain similar as the trajectory continues along the line which is checked by plotting standardized (studentized) residuals against unstandardized predicted values.
vi. There should be no significant outliers, high leverage points or highly influential points in the variables representing unusual observations.
vii. The residuals should be approximately normally distributed.

4.6.2.2. Modelling the Multiple Linear Regression Model in Stata

In theory, the 7 assumptions must be met by the data being used to run the multiple linear regression model. However, some methods violate some of the assumptions of the multiple linear regression model, such as the complex survey data analysis methods which were used in this study and implemented using the svyset command system in STATA (Oyeyemi, Adewara and Adeyemi, 2010). When data is analysed taking into consideration the complex survey design, the modelling systems aims to ensure that point estimates and standard errors

With survey data, the MLR assumptions that cases are independent of each other are violated, with the result that several diagnostic statistics such as Model LR Chi^2, Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC) are not generated. Wald tests instead of the LR Chi^2 are then used to make contrasts.

The decision to use complex survey analysis methods in this study were influenced by the need to use the national representation design parameters of the NIDS dataset, which was prepared to be representative at the national level (Brophy *et al.*, 2018). The use of complex survey design was also based on practical grounds since the model was using a large number of variables, the focus was placed on obtaining precisely positioned point estimates and associated standard errors which complex sampling design analysis makes possible (Oyeyemi, Adewara and Adeyemi, 2010; Farhat and Robb, 2014).

The linear regression model focused on the comprehensive digital index and its sub-indexes as response variables with socioeconomic variables, social exclusion, human capital, job competency and other demographic variables as explanatory variables. Explanatory variables were removed or retained in the model based on their respective probability values as displayed in the regression model output. The Wald test was used to determine the statistical significance of each explanatory variable at the 5% level of significance, with variables having Prob>F as reported in the Wald test results being removed from the analysis. The Wald test is similar to the t-test and works well in the testing of variables in complex survey designs.

Table 5: Regression Model Comparisons: With Complex Survey Design (1) and Normal unweighted Model (2)

```
Survey: Linear regression

Number of strata =  53                          Number of obs   =      7,296
Number of PSUs   = 401                          Population size = 13,972,673
                                                Design df       =        348
                                                F(28, 321)      =      39.55
                                                Prob > F        =     0.0000
                                                R-squared       =     0.5386
```

comms_asset_index	Coefficient	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	-.4905742	.146645	-3.35	0.001	-.7789962	-.2021522
2.gender_var	-.0732066	.1099465	-0.67	0.506	-.2894499	.1430367
population_grp						
2	.8012524	.291101	2.75	0.006	.2287138	1.373791
3	1.326555	.6815295	1.95	0.052	-.0138802	2.66699
4	1.987516	.3134692	6.34	0.000	1.370984	2.604049
cert_financialserv	-.0717829	.0547302	-1.31	0.191	-.1794265	.0358606
highlyq_proff	.4013192	.1232726	3.26	0.001	.1588661	.6437724
exp_construction	.0374339	.0225575	1.66	0.098	-.0069323	.0818001
exp_translog	.0033112	.0201565	0.16	0.870	-.0363328	.0429551
technical_skills	.1241347	.1439637	0.86	0.389	-.1590138	.4072831
matric_unskilled	-.0161258	.0234026	-0.69	0.491	-.0621541	.0299026
sedentary	-.1324318	.0451178	-2.94	0.004	-.2211697	-.0436939
marg_active	.003243	.0320551	0.10	0.919	-.059803	.0662891
serv_access	.1275525	.0265969	4.80	0.000	.0752416	.1798634
labmkt_act	-.1731912	.0380582	-4.55	0.000	-.2480443	-.0983381
access_devopp	.1282353	.0339533	3.78	0.000	.0614559	.1950148
mod_prefleave	-.1464325	.030015	-4.88	0.000	-.2054662	-.0873989
commercial_inf	.6353211	.0574739	11.05	0.000	.5222811	.7483611
stable_hsehld	.255766	.076275	3.35	0.001	.105748	.4057839
noinf_access	.0134962	.0475403	0.28	0.777	-.0800063	.1069986
poor_infserv	-.0860671	.0440779	-1.95	0.052	-.1727597	.0006255
urban_res	.1009162	.0387425	2.60	0.010	.0247173	.1771151
urbanpoor_hsng	-.0075796	.0727098	-0.10	0.917	-.1505856	.1354264
medskills_comm	.1810598	.0602665	3.00	0.003	.0625273	.2995922
lowskills_extprcomp	.1982734	.0503662	3.94	0.000	.0992129	.297334
lowskills_poorlangcomp	.1563132	.0435378	3.59	0.000	.0706828	.2419436
comms_skills	.1900508	.0480063	3.96	0.000	.0956317	.2844699
highskills_complit	.2123105	.0512661	4.14	0.000	.1114801	.313141
_cons	.6148367	.3147884	1.95	0.052	-.0042903	1.233964

Source	SS	df	MS			
				Number of obs	=	7,296
				F(20, 7275)	=	374.99
Model	39193.6306	20	1959.68153	Prob > F	=	0.0000
Residual	38019.337	7,275	5.2260257	R-squared	=	0.5076
				Adj R-squared	=	0.5063
Total	77212.9676	7,295	10.5843684	Root MSE	=	2.2861

comms_asset_index	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	-.3815165	.0792952	-4.81	0.000	-.5369582	-.2260748
2.gender_var	-.000568	.0563304	-0.01	0.992	-.1109919	.109856
population_grp						
2	.4059293	.0843489	4.81	0.000	.2405811	.5712776
3	1.263289	.2346266	5.38	0.000	.803353	1.723225
4	2.735132	.1296678	21.09	0.000	2.480945	2.989318
highlyq_proff	.1700366	.0262681	6.47	0.000	.1185435	.2215297
sedentary	-.0810048	.0210758	-3.84	0.000	-.1223194	-.0396902
serv_access	.093809	.0118298	7.93	0.000	.0706192	.1169988
labmkt_act	-.114591	.0160132	-7.16	0.000	-.1459816	-.0832004
access_devopp	.097941	.0098105	9.98	0.000	.0787096	.1171724
mod_prefleave	-.1310262	.014797	-8.85	0.000	-.1600327	-.1020197
commercial_inf	.6603051	.0228809	28.86	0.000	.6154518	.7051584
stable_hsehld	.2903042	.0240827	12.05	0.000	.243095	.3375133
poor_infserv	-.0342637	.0227748	-1.50	0.133	-.0789089	.0103816
urban_res	.0281189	.023986	1.17	0.241	-.0189007	.0751385
medskills_comm	.1344583	.0271164	4.96	0.000	.0813023	.1876143
lowskills_extprcomp	.1346732	.0224611	6.00	0.000	.0906428	.1787035
lowskills_poorlangcomp	.1029859	.0207505	4.96	0.000	.062309	.1436629
comms_skills	.1147776	.0222172	5.17	0.000	.0712254	.1583297
highskills_complit	.12335	.0192324	6.41	0.000	.0856489	.1610511
_cons	.5898411	.08266	7.14	0.000	.4278036	.7518786

Some differences are noticeable in the two outputs, in Table (1), the results show that the sample represents a population of 13.9 million South Africans, while only 7200 in the normal regression model. The survey results do not present an analysis of variance table as in Table (2), the normal regression model. The coefficients are different showing the effect of clustering and stratification in survey design and its effect on significance tests and confidence intervals.

The modelling approach was also used to test changes in the response variable for every 1 unit increase in each of the feature variables as shown by the results below. The forecast showed that the unit changes in explanatory variables had an impact on the state of the response variables, and this analysis was conducted for all the multiple linear regression models used in the inferential analysis.

Table 6: Exponentiated Coefficients of Regression Model

```
Survey: Linear regression

Number of strata =  53                            Number of obs   =      7,296
Number of PSUs   = 401                            Population size = 13,972,673
                                                  Design df       =        348
                                                  F(19, 330)      =      50.23
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.5360
```

comms_asset_index	exp(coef.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	.6107526	.0855306	-3.52	0.000	.4637095	.8044233
population_grp						
2	2.20494	.604357	2.88	0.004	1.2861	3.780235
3	3.84793	2.520171	2.06	0.040	1.061192	13.95277
4	7.253902	2.325826	6.18	0.000	3.860981	13.62843
highlyq_proff	1.417882	.1378247	3.59	0.000	1.171145	1.716602
sedentary	.8761952	.0399149	-2.90	0.004	.8011045	.9583243
serv_access	1.133903	.0295284	4.83	0.000	1.077288	1.193492
labmkt_act	.8387948	.0323847	-4.55	0.000	.7774587	.9049698
access_devopp	1.140092	.0378098	3.95	0.000	1.0681	1.216935
mod_prefleave	.8620705	.0271376	-4.71	0.000	.8103149	.9171319
commercial_inf	1.909824	.1045504	11.82	0.000	1.714877	2.126933
stable_hsehld	1.297757	.0941247	3.59	0.000	1.12523	1.496737
poor_infserv	.9160988	.0439413	-1.83	0.069	.8336262	1.006731
urban_res	1.099205	.0427063	2.43	0.015	1.018339	1.186492
medskills_comm	1.206932	.0728689	3.12	0.002	1.071796	1.359108
lowskills_extprcomp	1.222358	.061149	4.01	0.000	1.107817	1.348741
lowskills_poorlangcomp	1.166126	.0515675	3.48	0.001	1.068988	1.272091
comms_skills	1.20693	.056889	3.99	0.000	1.10007	1.32417
highskills_complit	1.200203	.0507913	4.31	0.000	1.104351	1.304375
_cons	1.82575	.3572738	3.08	0.002	1.242486	2.682816

4.6.2.3.Diagnostic testing for the multiple linear regression model

As stated in the preceding section, using a complex survey design violates some assumptions of the multiple linear regression model, while the use of underlying survey design ensures that point estimates and standard errors of regression coefficients and other parameters are highly accurate (Farhat and Robb, 2014). For the numerous regression models which were run in this analysis (4 models for each wave for 5 waves of the NIDS data), for space reasons, in diagnostics, the distribution of the residuals is the only reported diagnostic results reported in Appendix 4, for regression models in Wave 1 and Wave 5 of the NIDS data.

Composite index variables were used in the analysis which was measured at the continuous scale meeting the requirements of assumptions 1 and 2 of the multiple linear regression model.

Diagnostic plots such as histograms and q-normal plots of residuals following regression analysis showed the presence of highly influential values in the underlying dataset. This was possibly due to unequal weighting implemented under complex survey design. This might also mean that heteroskedasticity might be present in the data. The shortcoming of regression modelling in this study is therefore not related to the limitations of the model, but to the underlying structure of the survey design which was incorporated in the analysis of data to undertake analysis at the national level for which the survey data was designed to bee valid (Brophy *et al.*, 2018).

The normal plots of the residuals showed the presence of influential observations in the data, in very low and very high values of the indexes. This was observed to be caused by the use of sampling design in regression analysis which as expected and explained earlier, violates the assumptions of normality of residuals. However, since survey design ensures more centred point estimates and standard errors that are closer to the true mean values, the models after being subjected to wald tests to remove insignificant values were reported in Chapter 5.

4.7. Reliability and Validity

The study utilizes two strands of data, quantitative and qualitative which have different procedures for establishing reliability and validity. In discussing these aspects of this research study, two separate discussions are provided, initially for the quantitative data analysis methods followed by the qualitative data analysis methodology employed. These are discussed in turn.

4.7.1. Reliability: Quantitative analysis

Reliability refers to the consistency and robustness of the findings of a study based on applied methods of analysis and interpretation of data (Given, 2008). Reliability and validity indicate how well a technique, method or statistical test measure something during analysis, with reliability focusing on consistency of the measure, while validity focusing on the accuracy of the measure (Heale and Twycross, 2015).

In this study, the quantitative methodology has been sufficiently documented on a step-by-step approach, clarifying each decision and step taken in both the preparation of the data, the preparation of the variables and the data analysis process. This was done to ensure that the research study can be replicated with ease. To this end, methodological procedures were documented, with their reliability measures documented against established thresholds, and while almost all statistical measures of reliability in the creation of index variables were below the thresholds, the methodological procedures have been documented and can be replicated in future studies, on better premises.

It must also be noted that PCA is normally applied in scaled data or with correlated factors/variables, such as Likert scale type data or psychometric-based measurement scales, where choice is made between normal PCA or polychoric PCA. In this study, the dataset was neither scaled nor of an ordinal nature and recourse was made to use PCA with uncorrelated factors, hence the use of multiple indexes instead of reducing all variables to a single index for analysis. This was done to improve the reliability of the computed index in capturing not one but multiple dimensions of the phenomena under consideration according to the distribution of variability among the component (composed of groupings of variables according to their correlations and variability).

Internal consistency was measured in this study during statistical analysis using Cronbach alpha and the Kaiser Merlin Olkin (KMO) measure of sampling adequacy (Appendix 2). On statistical grounds, the variables failed to meet thresholds thus failing to demonstrate internal consistency in the generation of index variables. In regression analysis, stability of the regression was ensured through re-testing the linear model using hypothesis testing and eliminating the insignificant variables, such that the reported measure of variability explained by the model, the r-squared statistic was established to be stable based on re-testing with the reported results of the regression model deemed stable.

4.7.2. Validity: Quantitative Analysis

Validity is concerned with a given study's instrumentality, specifically an inquiry whether the study results show that what was intended to be measured was measured. This will depend on the alignment of the constructs of the studies to the underlying theoretical propositions, or existing information, referred to as construct validity (Given, 2008:909). The extent to which a concept is accurately measured in a quantitative study (Heale and Twycross, 2015). This study can be demonstrated to have been undertaken within strongly established bases of validity.

Content validity is concerned with whether the instruments used in the study adequately covers all the content concerning the variable. In this study, there were no instruments used in primary data collection, however, instrumentality was a required standard in the creation of index variables. There was a need to ensure that generated indices covered to a higher degree of variability the aspects of the study that was being measured. To ensure that content validity was established, there was a move from the norm in the studies of using a single component with the highest eigenvalue (a measure of variability) (Vyas and Kumaranayake, 2006; Howe, Hargreaves and Huttly, 2008; Tareq *et al.*, 2021), towards using multiple index variables generated from subindexes based on the variability distribution of the computed indices. This enabled the researcher to account for all the aspects of a given phenomenon that was being measured, particularly with the core variables, such as socioeconomic status, social exclusion, digital index, human capital and multidimensional energy index among others.

Construct validity, refers to the possibility of drawing inferences about test scores related to the concept being studied (Heale and Twycross, 2015), for example, the index on the comprehensive digital asset index, whether it could establish differences between groups within the population depending on the level of the index associated with each population group. In the findings of the study, it was observed that the results established through computation were aligned with findings established in other studies, across the years aligned with the waves of the NIDS dataset. This was very true of the distribution of access to computer skills, human capital, labour market participation and other variables used in the analysis (Chapter 5: findings on quantitative research). Thus, theoretical positions were not only adopted in the construction of the variables and the design of the research, the findings were tested against established findings during analysis and post-analysis in the integration of the findings.

4.7.3. Credibility and Trustworthiness: Qualitative data

The most important attribute for assessing a qualitative study is quality understood in the sense that qualitative analysis achieves the purpose of generating an understanding of a phenomenon (Golafshani, 2003). In other words, the researcher was primarily concerned with persuading the audiences that the findings of the study are worth paying attention to as suggested by Lincoln and Guba (1985, 290). To this end, the focus is placed on the concepts of credibility, neutrality and confirmability essential to the criterion of quality.

Credibility addresses the fit between participants' views and the researcher's representation of them (Nowell *et al.*, 2017). In this study, credibility was ensured through persistent observation in which the researcher developed the codes, commencing with a template coding manual, with the concepts and the core categories helping to delimit the focus of qualitative analysis as well as examining the characteristics of the data. Through constant comparison, reading and reading the data, analysing, theorizing and revising the concepts accordingly, meaning that the final themes selected and substantive theoretical propositions were established after careful thought and consideration. The researcher compared the themes with the original data, to ensure that the substantive qualitative findings were aligned with the original ideas of the participants while providing the intended depth of insight.

Dependability is the process of ensuring that the research process is logical, traceable and documented (Nowell *et al.*, 2017). In this study, every aspect of the qualitative research procedures was documented, to ensure that the audiences can examine the research process, and are better able to judge the dependability of the research. The detailed documentation was done to ensure that the research process is auditable. To this end, to ensure that a comprehensive audit trail was created, the design of the coding template was discussed, the key concepts behind the decisions that were made in the development of codes, in the integration of codes into themes, and the process of writing and summarizing the substantive theory so that the decisions and choices made by the researcher can have a demonstrable rationale. A study and its findings are auditable when another researcher can follow the decision trail (Ryan-Nicholls and Will, 2009), or another researcher given the same data, perspective and situation could reach the same or comparable but not contradictory conclusions (Koch, 1994). The records of the raw data in both video and transcript format were preserved for reference purposes, and through the use of the NVivo software, coding decisions were documented as properties (descriptions) to each coded piece of data, so that with each code, other researchers can understand the meaning of the code and the decisions behind the development of that code.

4.8. Ethical Considerations

This study utilized secondary data sources as explained in the foregoing sections (4.5), and the researcher undertaking the study was granted ethics exemption by the University of KwaZulu Natal, Higher Degrees Ethics Committee. The Ethics exemption letter is attached in Appendix 1, permission to use the National Incomes Dynamics Study data is also attached in Appendix 3.

4.9. Chapter Summary

In this chapter the research methodology has been discussed, focusing on the adopted philosophy of pragmatism and its application in this research study. Adopting a pragmatist philosophy of thinking, a mixed-methods approach was adopted employing an integration of quantitative and qualitative methods in meeting the objectives of the study. It was demonstrated that the pragmatist framework of thinking provides the requisite basis for integrating quantitative and qualitative methods. An innovation the researcher took in the design and undertaking of the study, has been the use of two datasets at different levels of aggregation, the local level for quantitative data, and the international level for qualitative data. The assumption that was made, was that what is observed at the international level is a result of an aggregation of local decisions and policies, such that even with aggregation at two different levels, there is enough interaction to help understand the occurrences at both levels of analysis. The researcher united the two levels using a well thought out theoretical framework, which was then operationalized in this chapter detailing the implementation of the research methodology.

4.9.1. Limitations of the research methodology: Quantitative

The index variables which were computed for analysis in the study failed largely to meet the theoretical thresholds of the statistical methodologies employed, the PCA. As presented in the tables presented recording measures of statistical adequacy, both the Cronbach alpha and the KMO measures were normally below acceptable thresholds at the theoretical levels. However, the researcher decided that the applied methodology of principal components analysis was satisfactory in the computed indexes at the operational level, as the resulting variables captured all the content as measured in other studies. Furthermore, using multiple indexes on each composite variable, ensured that every aspect of the phenomenon being considered was measured and incorporated into the analysis. Demonstrably, on statistical grounds the composite indexes fall short, however, the conclusions being reached through analysis using those same indexes, are comparable to findings established in other research studies such as those in poverty analysis, social welfare and economics as demonstrated in Chapter 5.

4.9.2. Limitations on research methodology: Qualitative

The analysis was influenced largely by the researcher’s background in economics, such that the researchers from other academic backgrounds might not reach the same conclusions at a deeper level of analysis. However, at the semantic level, there would be largely no differences between the conclusions of the researcher and that of other researchers. In the next two chapters, a presentation and interpretation of the quantitative, and qualitative findings are presented as Chapter 5 and 6, respectively.

The quantitative analysis is representative at the national level; thus, the results are generalisable across South Africa. While the quantitative results are generalisable at the national level, the positioning scope of the qualitative findings in this study is ambiguous, due to the nature of the participants, however, the decision was to treat the analysis as reflective of the conditions of advanced societies. Thus, the results are inferentially applicable to the South African economy. The assumption made was that South Africa is a net technology consumer, with no influence on the nature of the technologies adopted beyond ethical regulation. The qualitative analysis was thus used to provide insights based on this very strong assumption which can be disproved. The qualitative analysis is not representative of the general views across the globe, with the findings being taken to be limited insights mostly based on the experiences of developed countries. Future studies will require a more focused analysis of DT based on the experience of emerging economies, thus more focused data collection and analysis.

In constructing the composite variables used in the quantitative analysis of the national income dynamics study data, all the variables failed to meet the thresholds of sampling adequacy using both Cronbach alpha and the Kaiser-Meyer-Olkin measure of sampling adequacy. The six key variables, the digital index, the socioeconomic index, the social exclusion index, the job competency index, the upskilling index and the human capital index, all showed below threshold values for both measures, indicating that the quantitative dataset was of inadequate sample for the methods the researcher selected. The recourse could have been to use alternative methods for index variable construction or increase the dataset, which was not done in this study. While, the variables failed on measures of sampling adequacy thus negatively affecting the reliability of quantitative results, the results of the quantitative analysis aligned with findings in the extant literature, particularly on poverty in measures such as socioeconomic index and social exclusion. Thus, the decision was made to retain the index variables.

Understanding the manifestation of DT in South Africa is going to be important in the design of interventions and policies, particularly those directed at addressing the existing physical divide. While the nationally-representative NIDS can be adequate, there is a need for a dataset on DT that accurately traces the changes in the digital divide across South Africa. There is a need to incorporate the perspectives and context of the most vulnerable so that context-based technological development and adoption can be done with their contexts in perspective. There is therefore a need for research into the broader contexts of the vulnerable and those at risk of displacement so that the design of technologies and their incorporation can be designed with minimal effects on these population groups.

CHAPTER 5: PRESENTATION AND INTERPRETATION OF QUANTITATIVE ANALYSIS FINDINGS.

5.1. Introduction

The findings from the analysis of the data as explained in section 4.6.3 are presented in this chapter and focus on the first objective of the study giving a descriptive and inferential analysis of socioeconomic indicators and variables concerning digital transformation. The results of the descriptive analysis are presented in charts showing the parametric mean of the distribution while the results of the inferential analysis are presented in regression tables. In the analysis, the metric of interest being tracked is the mean index, which shows average changes across time in the various indices, from wave 1 through wave 5.

5.2. Objective 1: The socioeconomic dynamics in the context of digital transformation.

In the theoretical model presented in Chapter 2, it is stated, socioeconomic dynamics of societies are initial conditions that influence the capacity of individuals, households or regions to adapt to pervasive changes affecting the generation or maintenance of material and qualitative welfare. The first objective of the research study sought to provide a clear profile of these initial conditions, starting with the year, 2008 with NIDS wave 1 and trace the changes in the socio-economic dynamics across the years culminating with NIDS wave 5 in the year 2017. There was no attempt to undertake an exhaustive analysis of all socioeconomic variables with the focus being placed on the variables that were informative of the changes in socioeconomic conditions of individuals, households and regions in South Africa. In presenting the results, the variable indicating population grouping is used as the basis for comparison, in univariate and bivariate analysis. This was done since the primary focus was to show the state of these initial conditions in South Africa, across and over time so that targeted interventions can be placed within the broader context of the South African socio-economic realities.

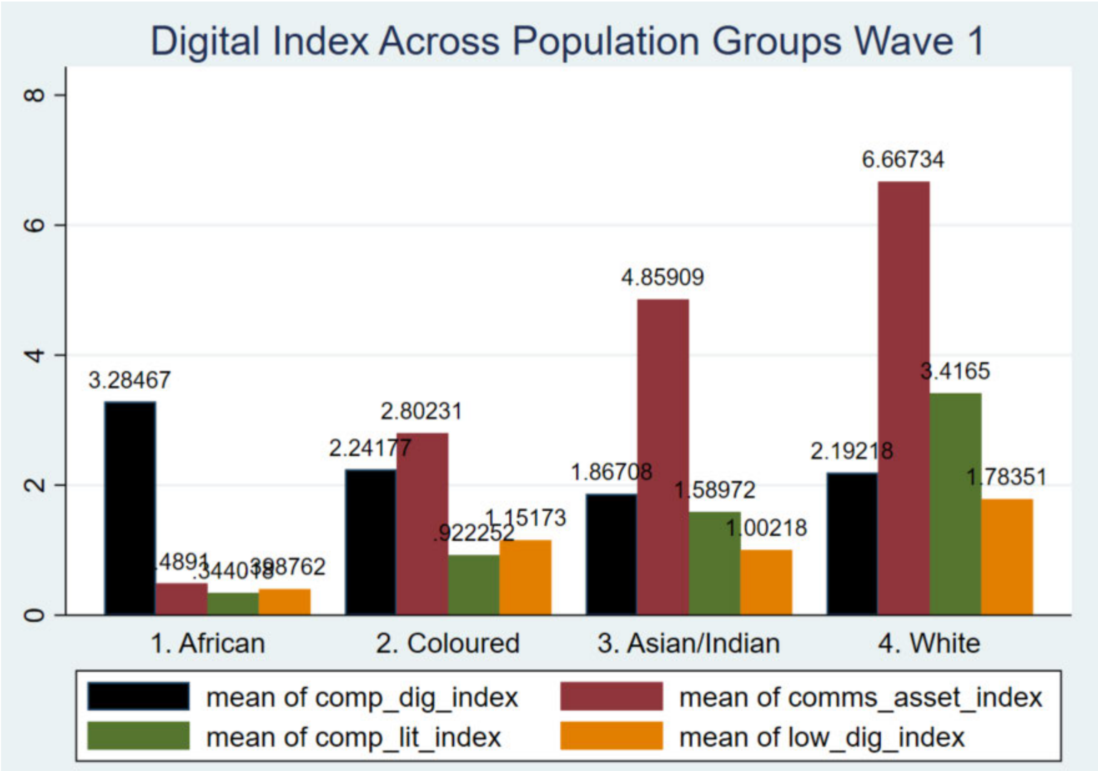
5.3. Descriptive analysis of National Income Dynamics Waves 1-5

5.3.1. Digital asset index across population groups

The digital asset index was decomposed into 4 separate indexes, the comprehensive digital asset index focused mostly on access to digital devices such as smartphones, computers and digital satellites, however, the index reflected extremely high loadings for access to smartphones The communication asset index that added other higher-level devices such as computers, the computer literacy index that added knowledge of computers and finally the low digital index defined by lack of access to communication devices. As shown in figure 2 below, showing the mean indexes across the four population groupings, it can be seen that Africans have a higher mean for the digital asset index when compared to other population groups. This shows the increased access to digital smartphones and telephonic devices among the African population group. This first component of digital access has been the subject of several studies, discussing ICTs for development and focused on access to digital phones and communication systems (Conradie D.P., Morris C., and Jacobs S.J., 2003; Akinsola, Herselman and Jacobs, 2005; Gillwald, Mothobi and Rademan, 2018). The analysis of this component of the digital index aligns with findings in these other studies, while the further decomposition of the digital index to assess other forms of digital access differentiates this present study.

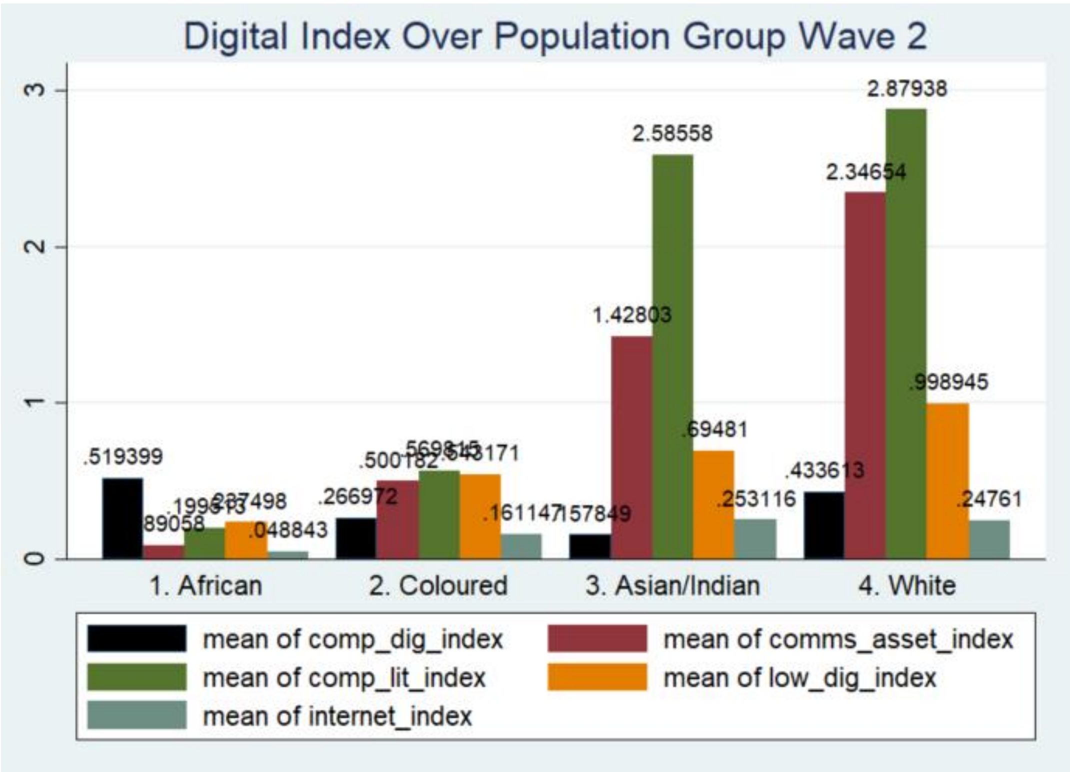
In other components of the digital index, the African population group performs generally poor than other population groups, given that these other indexes demonstrate access to computers, computer literacy and internet access. At the time of wave 1, the white population group showed greater access to communication assets such as computers as well as high stocks of digital skills and computer literacy as shown by the highest mean on the communication asset index attributable to the group. The analysis showed a very low mean for access to digital skills for Africans which can proxy lower participation levels in high-end digital communities for instance technology development communities like software programming or development. This contributes towards understanding skills dynamics in the service sector where the African population group feature prominently in lower-skilled occupations of the service industry while other groups dominate the high skills sectors and consequent patterns of the income distribution (Hunter and Hachimi, 2012; Burger, Steenekamp, *et al.*, 2015; Kahn, 2015). According to the study by Kahn (2015), the shortage of high-end skills has persistent with a racial profile with progress hampered by institutional challenges and crippling individual-level dynamics. These individual and institutional dynamics are shown in this study to be socioeconomic dynamics of individuals inhibiting skills development.

Figure 2: Mean of Measures of Digital Index across population groups



Source: Own calculations using NIDS Dataset

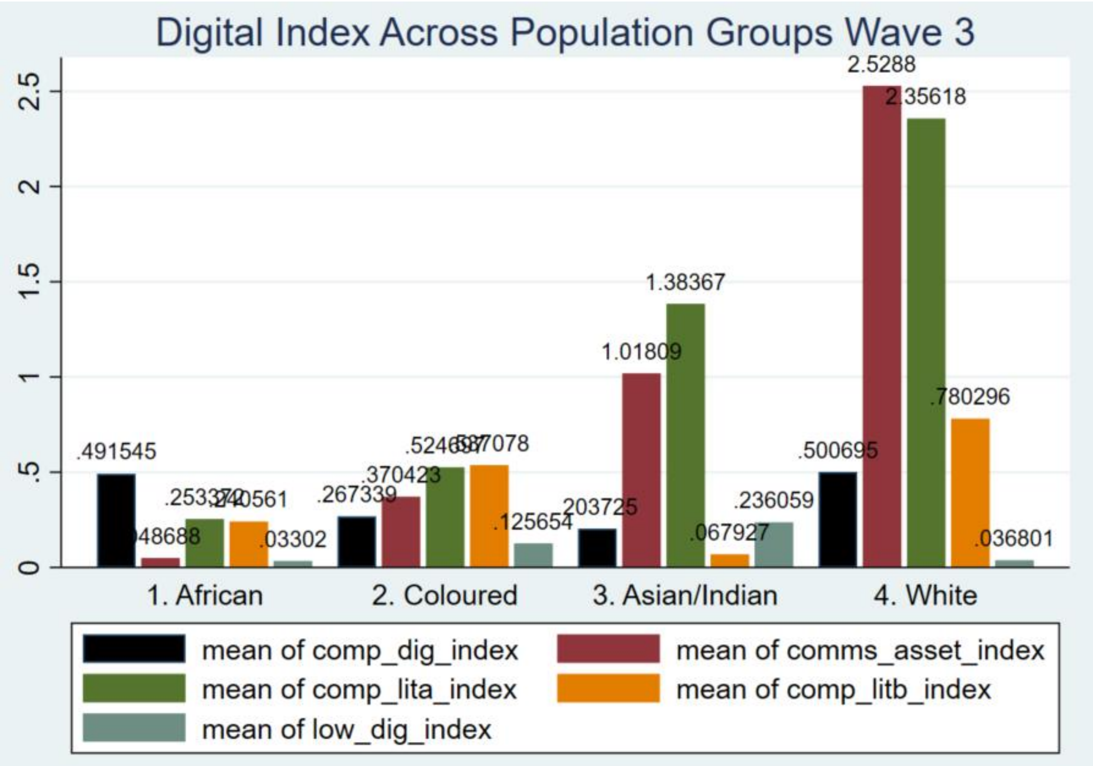
Figure 3: Digital Index Across Population Groupings Wave 2



Source: Own calculations using NIDS Dataset

Across wave 2 shown in figure 3, the relative importance of the digital asset index, which loaded heavily on access to cell phones declined as can be seen that even among the African population group which had the highest mean index, fell to below 1, while other indexes further worsened showing a decline in overall digital access. Over the same period, however, the Asian/Indian and White population groups gained significantly in the communication asset index, the computer literacy index and the low digital index which showed basic computer skills. Thus, within these groupings there was demonstrated higher access and control over digital assets and skills, while there is observed decline for the African population group. The analysis also reveals the change in index values from wave 1 to wave 2 and so forth, such that the mean indexes of the measures begin to show the marginal change in the index for each population group. Existing studies have also shown that ICTs play a key differentiation role in the current state of the dual South African educational system and continue to shape labour market dynamics (Akinsola, Herselman and Jacobs, 2005; Leibbrandt *et al.*, 2010; Kimani, 2015).

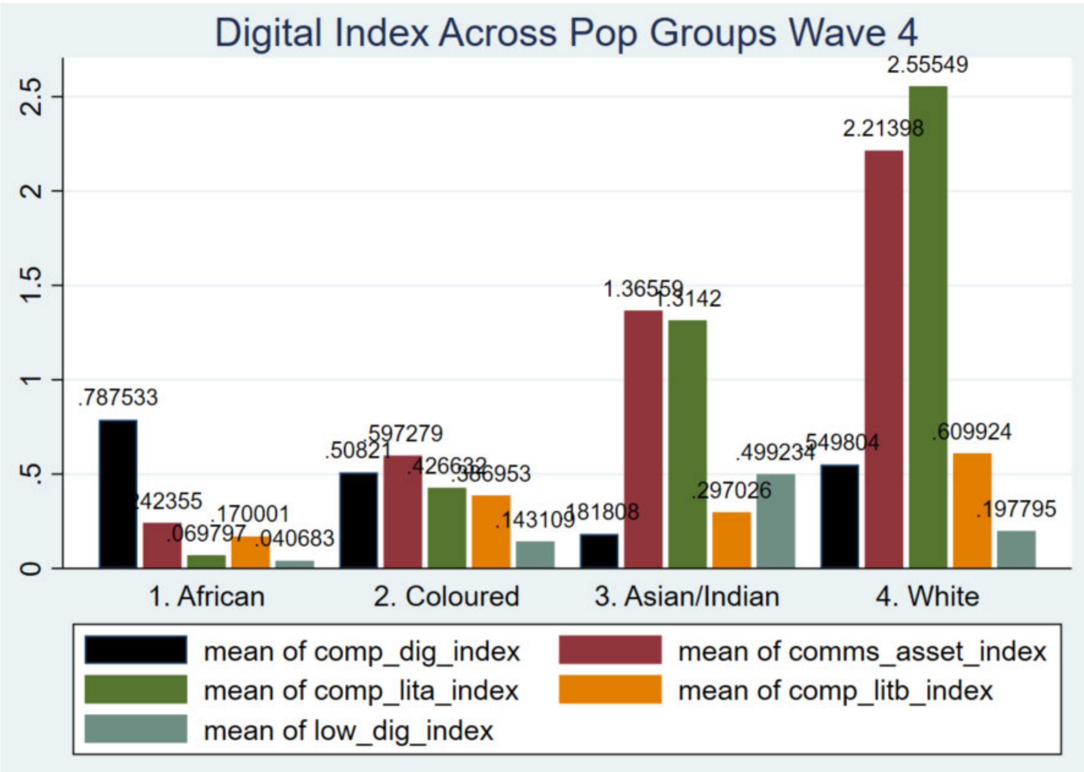
Figure 4: Digital Index Across Population Groups, Wave 3



Source: Own calculations using NIDS Dataset

In the analysis of wave 3 of the data shown in figure 4, the findings show that the mean of comprehensive digital index remained high for the African population group, yet was surpassed slightly by that for the Whites. The marginal change in the index shows a decline from its level in wave 2. The mean for the communication asset index further worsened for the African group, while it remained higher for the White, Asian/Indian and Coloured population groups. The data in wave 3 allowed for a decomposition between advanced computer skills (comp_lita) and basic computer skills (comp_litb), for which the African population group continued to perform poorly. Asian/India and White population groups continued to excel in the communication asset index as well as access to advanced computing skills. This is quite interesting given that Wave 3 of the National Incomes Dynamics Study was conducted in the 2 years leading to 2012 (Brophy *et al.*, 2018), a few years before the Davos 2016 discussions on the developing digital transformation. This could have demonstrated a shift in thinking about the future direction of the economy and its requirements among the White and Asian/Indian population groups. A study and a report have also demonstrated sectoral changes in the South African economy around this time with the increasing importance of the service sector and digital technology-based innovation (StatsSA, 2012; Bhorat *et al.*, 2015).

Figure 5: Digital Index Across Population Groups, Wave 4

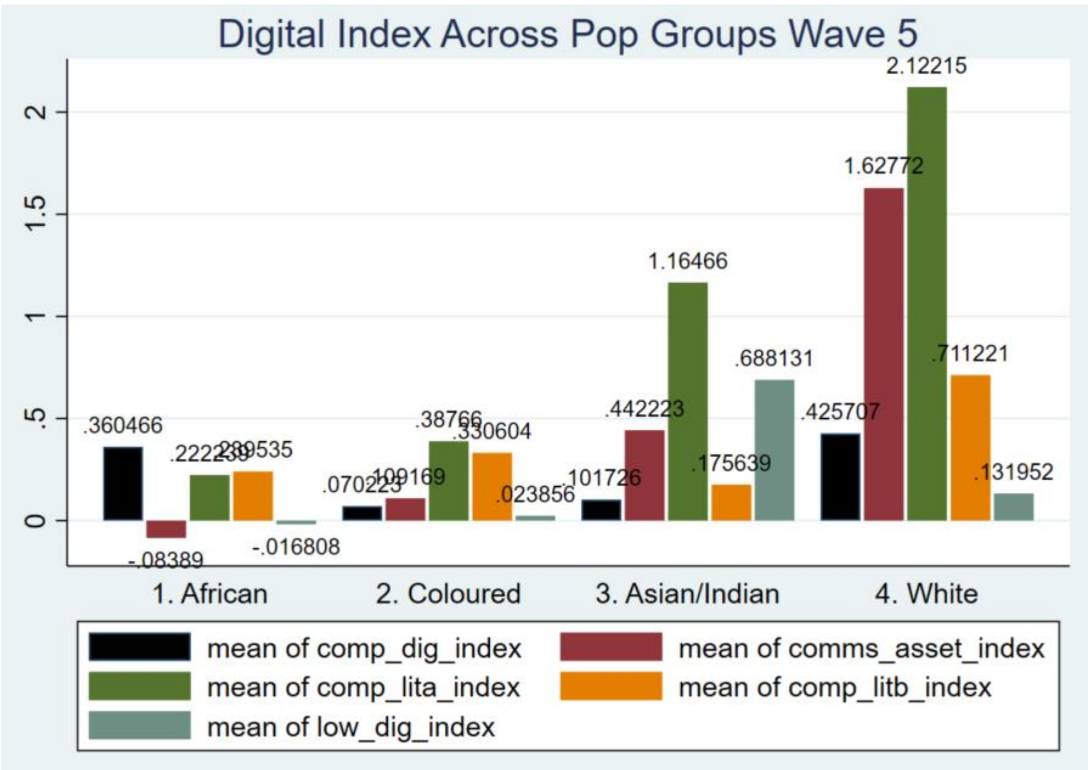


Source: Own calculation using NIDS dataset.

In the analysis of wave 4 of the data, the comprehensive digital index improved marginally by a few decimal points for the African population group as shown by the higher mean index when compared with its marginal level in wave 3. The marginal change in the communication asset index and the advanced computer skills index, remained roughly constant for African as well as for other population groups, with slight improvements for the Coloured population group when compared with statistics for Wave 3 in figure 4. Thus, the digital divide can be seen to be following a group profile, with higher access for some groups and poor access for others.

In Wave 5 (figure 6), the analysis shows a further worsening of the communication asset index for the African population group as shown by a negative mean index and also worsening of the advanced computer skills index (comp_lita) and the basic computer skills index (comp_litb). While the communication asset index and the advanced computer skills index remained high for Asian/Indian and White population groups although the mean change in the index was lower. Thus, the analysis of the change and distribution of the digital index across population groupings shows that in indexes that have remained largely the same across population groups, White and Asian/Indian population groups have more access to digital assets and skills than African and Coloured groups, showing the group dynamics of the digital divide, across South Africa over time. This racial dynamic behind the digital divide has been identified in other studies (Bornman, 2016; Lembani *et al.*, 2020) and in line with this study argue that the digital divide contributes to social inequities and divided development opportunities. Digital transformation cannot render equal opportunities given the existence of these digital divides and consequent socio-economic challenges.

Figure 6: Digital Index Across Population Groups, Wave 5

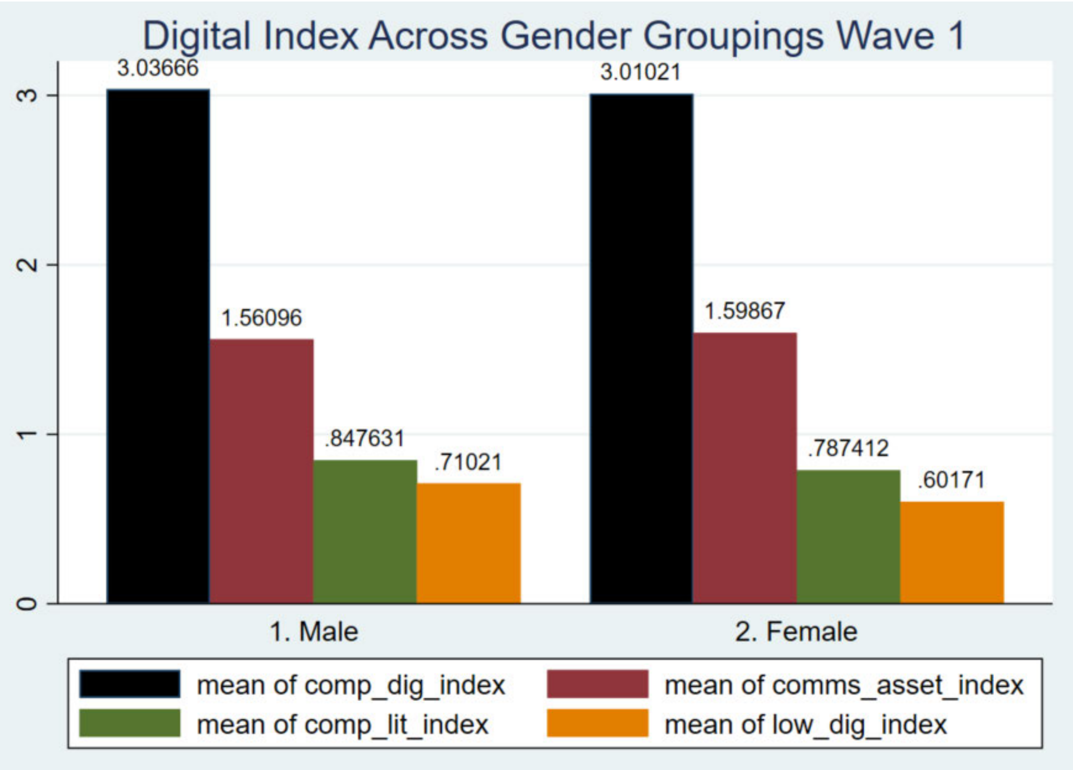


Source: Own calculations using NIDS Dataset.

5.4. Digital Index across Gender categories

While understanding the digital index across population groups is quite insightful, there is a need to also understand some aspects of the distribution across gender, thus a gendered analysis of the digital index was undertaken. In Wave 1, the analysis of the data showed that there were no significant gendered differences in the digital asset index (which loaded heavily on access to cell phones). The gendered analysis of the comprehensive digital index shown in figure 7 shows the existence of small differences in the mean between males and females. While, males demonstrate a higher mean the differences are small, which is attributable to the gendered analysis being omnibus across all population groups. A decomposition of gendered trends in the comprehensive digital index by population grouping is highly informative of the nature of the differences.

Figure 7: Digital Index across Gender



Source: Own calculations using NIDS dataset.

Table 7 shows that the gendered decomposition of the comprehensive digital index has significant differences for males versus females across population groups. African males have a higher mean than African females (3.26), and the same can be observed for other population groups. The differences in the mean are great for the African population group showing that females have less access to digital technology when compared to males. A similar decomposition was carried out across all 5 waves of the NIDS data to examine the population group characteristics masked by the reported gendered analysis. For the African population group, males had a higher mean for comprehensive digital access than females. This is significant since app-based digital integration is the existing phase of digital integration for many, the gendered inequities observed masked patterns of digital inequities likely to persist under the pervasive digital transformation (Shepherd, 2016; Abolhassan, 2017).

Table 7: Gendered Decomposition of Comprehensive Digital Index by Population Grouping.

Survey: Mean estimation

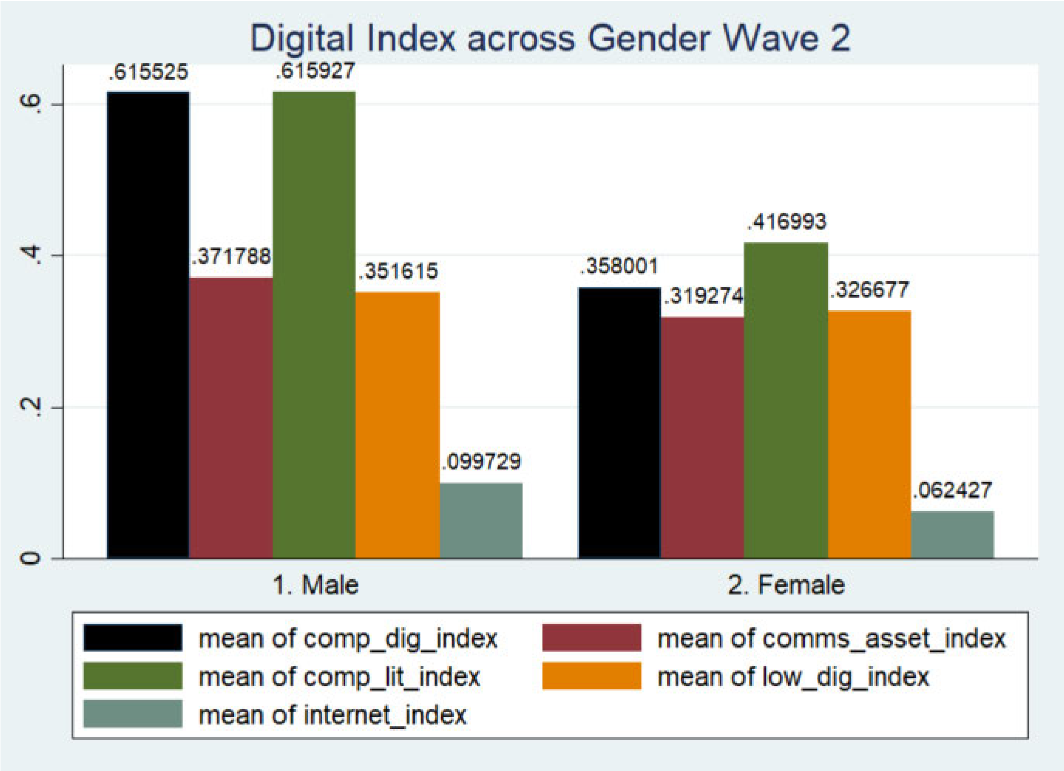
Number of strata = 53	Number of obs = 7,296
Number of PSUs = 401	Population size = 13,972,673
	Subpop. no. obs = 3,072
	Subpop. size = 6,748,962.9
	Design df = 348

	Mean	Linearized std. err.	[95% conf.	interval]
c.comp_dig_index@population_grp				
1	3.26346	.0337664	3.197048	3.329872
2	2.342454	.2170039	1.91565	2.769258
3	1.994261	.1941158	1.612473	2.376049
4	2.300283	.1343238	2.036094	2.564471

In wave 2 (figure 8 below), the analysis showed a higher mean value for males than females for the comprehensive digital asset index. Males also showed slightly higher access to communication assets as shown by the slightly higher mean for the communication asset index between males and females. The differences across all the four indexes making up the digital index when assessed across gender groupings showed slight differences, meaning that over the years spanning waves 1 and 2, the distribution of the digital index across population groupings did not change even when the analysis is decomposed for gender.

In the analysis in wave 2, the marginal change in the indexes shows a few differences of note. The marginal change in the comprehensive digital index was higher for males than for females and so is the marginal change in the computer literacy index, meaning more males were becoming computer literate than females. Males also exhibited a slightly higher marginal gain in the communication asset index, meaning that males had more access to computers, and other digital assets than females. Thus, the analysis in wave 2 of the data shows plainly the marginally growing digital divide across gender lines.

Figure 8: Digital Index across gender Wave 2



Source: Own calculations using NIDS dataset

The analysis argued that when consideration is given to access high-end digital devices and advanced technology skills, the African population performed poorly ad while gendered trends capture this difference the decomposition shows greater disproportion. In the decomposition of the communication asset index shown in table 8, Africans have the lowest mean index. This decomposition shows that while gendered differences exist with the African population group, the overall mean index for the African population group is very small when compared to other population groups. According to Table 8, this decomposition is across approximately 15.6 million South African male and female adults. A recent publication on women empowerment in KwaZulu Natal rural areas argued for the need for improvement in developmental status for women in rural areas in the advent of the fourth industrial revolution (Jiyane, 2021). The paper concluded that rural women needed better access to information and knowledge, however, this study shows that there is a dire need for the development of skills that can enable women to effectively use information and knowledge to harness opportunities of digital transformation.

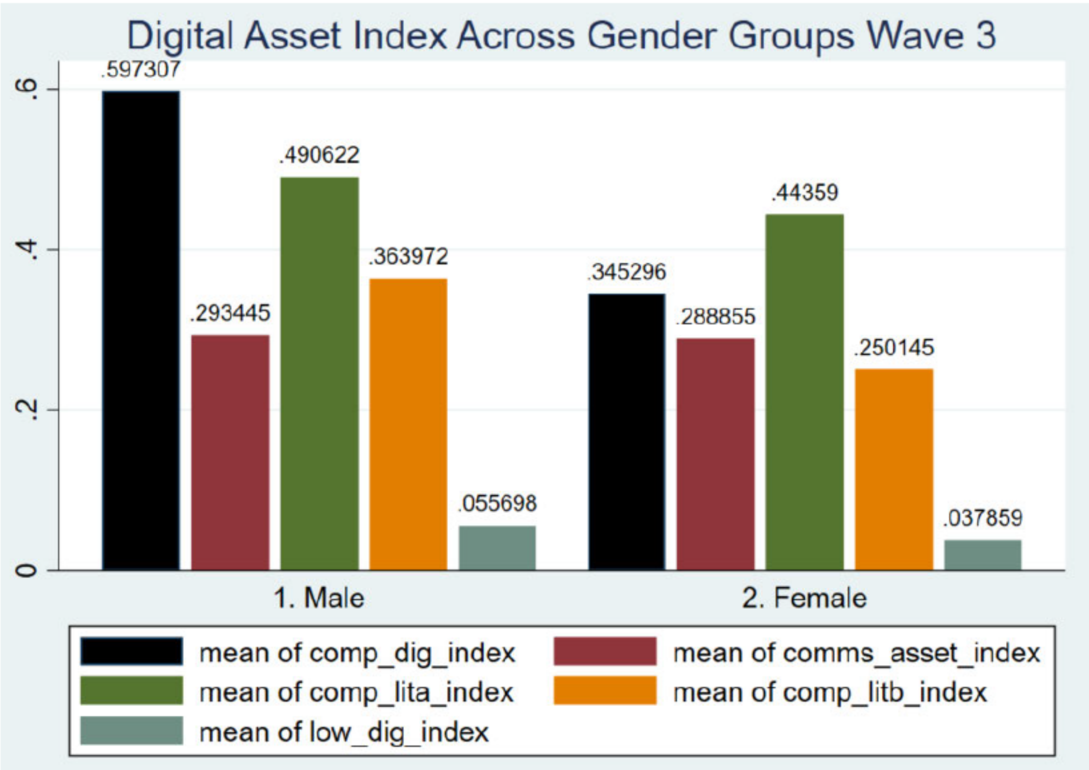
Table 8: Gendered decomposition of the Communication Asset Index for Wave 3 data

```
Survey: Mean estimation

Number of strata =     54                    Number of obs    =      5,940
Number of PSUs   = 5,940                     Population size  = 15,672,631
                                             Subpop. no. obs  =      2,905
                                             Subpop. size     = 8,414,854.2
                                             Design df        =      5,886
```

	Mean	Linearized std. err.	[95% conf.	interval]
c.comms_asset_index@population_grp				
1	.4587114	.0625323	.3361251	.5812976
2	1.37724	.2993054	.7904915	1.963989
3	2.867656	.9618749	.9820279	4.753284
4	6.679965	.7548529	5.200176	8.159754

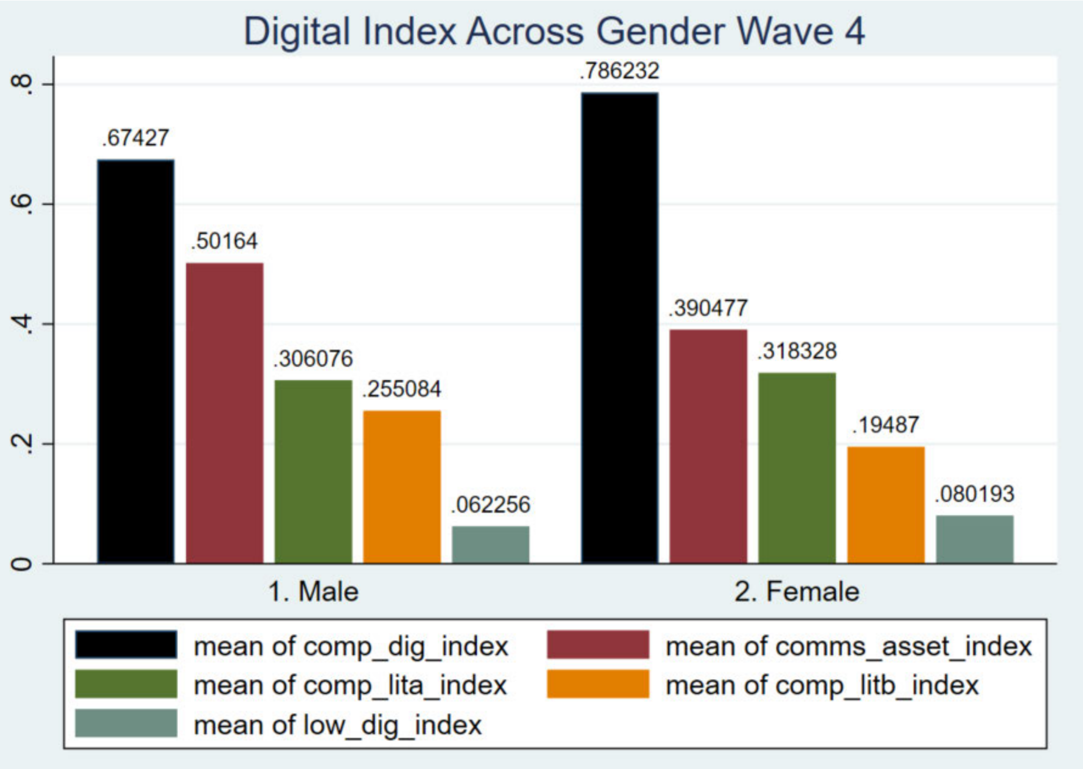
Figure 9: Digital Index across Gender Categories, Wave 3



Source: Own calculations using NIDS dataset

The analysis of wave 3 of the data shown in figure 9 examining the gendered trends of the digital divide, showed a slight decline in the marginal change of the indexes across gender. Males continued to have higher access to digital devices particularly smartphones, with a slightly larger change in the marginal index. The marginal index for change in access to advanced computing skills (comp_lita) showed slight improvement for females with a few decimal point differences from the marginal change in the index for males. Access to communication assets has slightly equalised shown by the relatively similar marginal index of change for both males and females.

Figure 10: Digital Index Across Gender Groupings, Wave 4

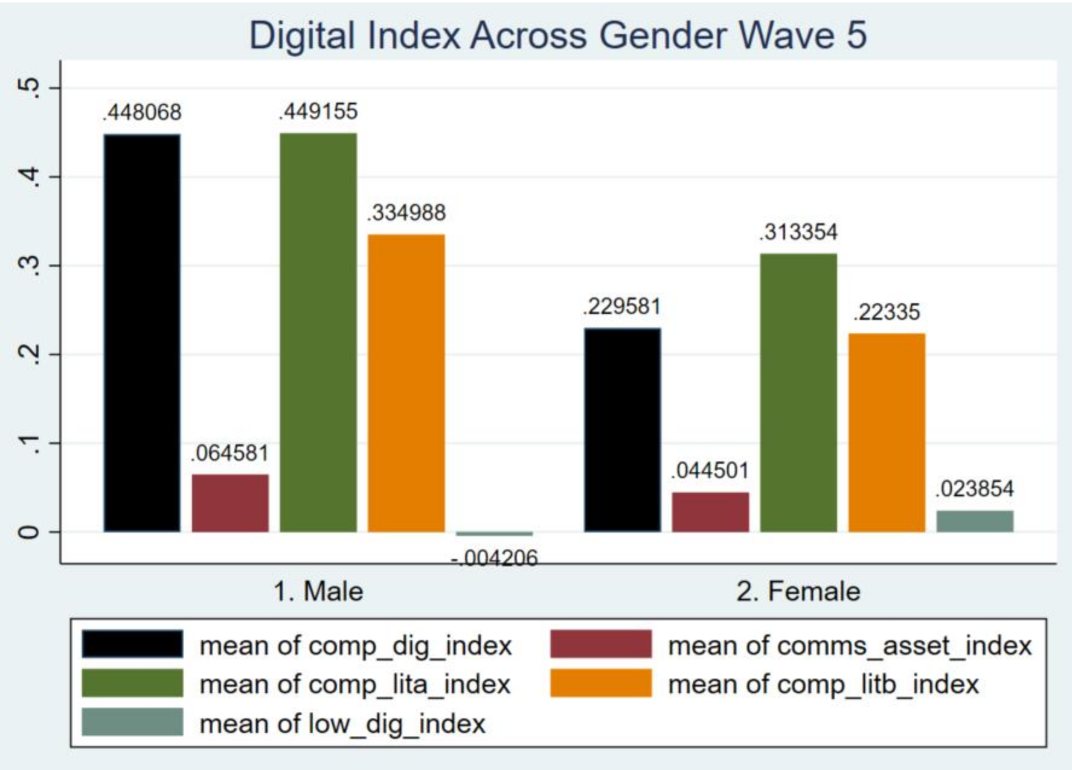


Source: Own calculations using NIDS dataset

The analysis for wave 4 as shown in figure 10 above shows a shift in the marginal change in the comprehensive digital index, with a slight advantage for females over males and a slight gain-in advantage for the computer literacy index (comp_lita) for females. The analysis shows that there was a slight increase in the ownership of smartphones by females shown by the higher marginal change in the comprehensive digital index. This showed increased ownership of smartphones which dominated the comprehensive digital asset index and a slight gain in advanced digital skills and use of computers for women. Males continued, however, to have more access to other communication assets such as computers, digital satellites and telephones and the internet, as shown by the high mean index for communication asset index.

The analysis of wave 5 of the data shown in figure 11, below shows some reversals as marginal change for the comprehensive digital index was higher for males than for females, meaning on average males showed greater access to smartphones than females. Males also showed a higher marginal change in access to advanced digital skills (comp_lita) than females, meaning more males engaging in computer-related skills development as compared to females. Men also showed greater access to basic computing skills than females (comp_litb). The higher marginal change in the low digital index for females than males shows that more females than males increasingly have less access to digital devices and skills. The analysis of the digital index across gender shows that there is a divide in access to digital assets, skills and general technologies that favour males as opposed to women. Men showed higher access to smartphones, the internet, telephones, computers, and computer skills both basic and advanced as shown by slightly higher on average indexes across the five waves of the national incomes' dynamics study data sets. Thus, the digital divide while not only exhibiting dynamics across population groups, also has a gendered trend that is biased against women.

Figure 11: Digital Index across Gender Groupings, Wave 5

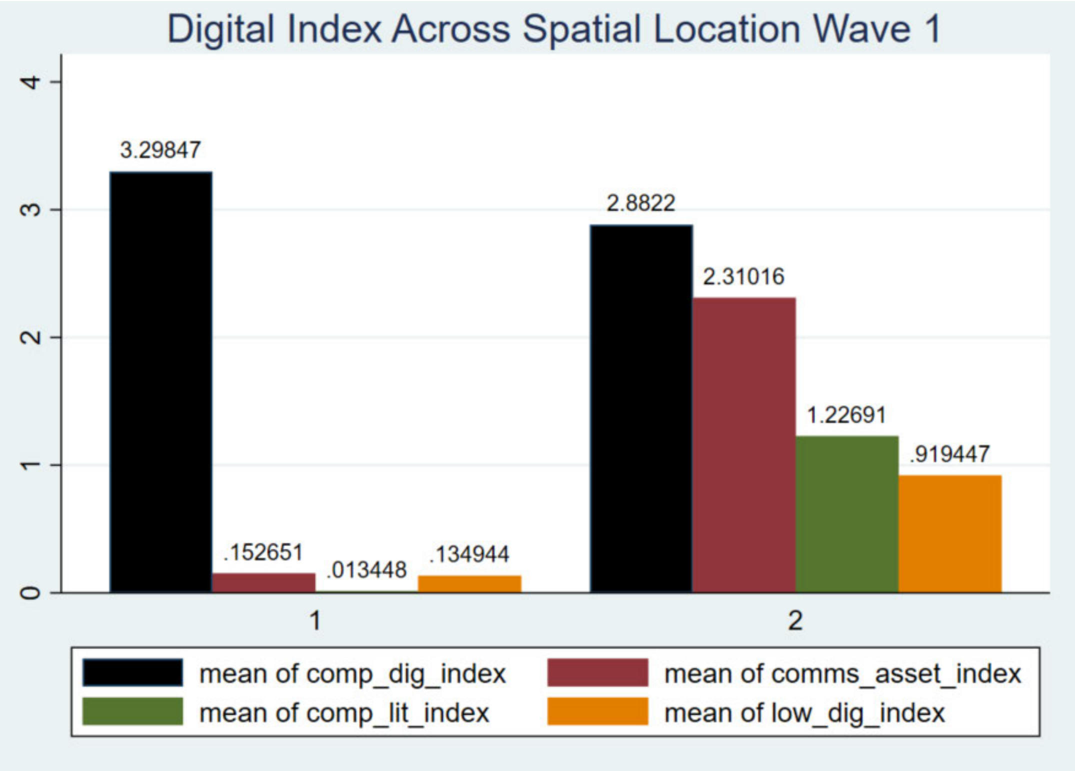


Source: Own calculations using NIDS dataset.

5.5. Digital Asset Index across spatial geography

The analysis was further extended to consider the spatial dynamics of the digital index. This was driven by considerations from previous studies on socioeconomic dynamics, that established a difference in infrastructure, access to services and so forth between urban and rural geographies (Leibbrandt *et al.*, 2010; Milbourne, 2010; Shepherd and Brunt, 2013). In the analysis of wave 1 of the data shown in chart 5.5.1, the comprehensive digital index had a higher mean for rural areas than for urban areas, which means that there was access to more cell phones in rural areas than urban areas during this period. However, concerning access to other digital assets, such as computers, satellites and the internet as well as access to both basic and advanced digital skills, the mean indexes were much higher for urban geographies than for rural geographies, reflecting the spatial digital divide.

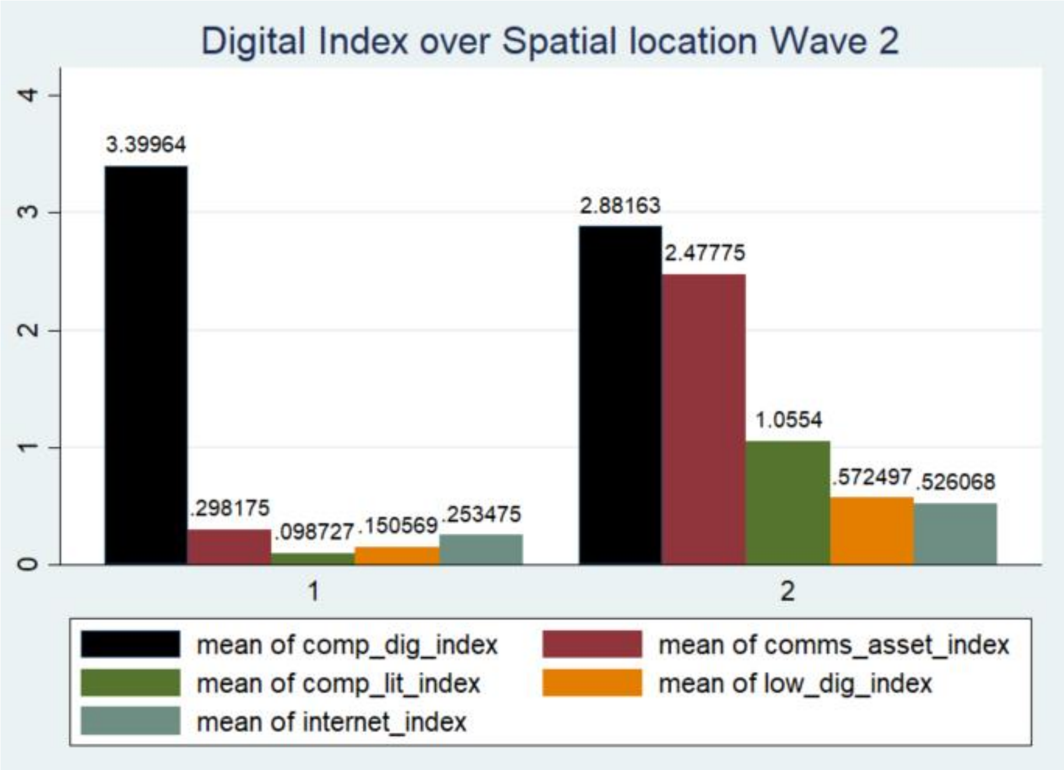
Figure 12: Mean Digital Index across spatial location (1=Rural, 2=Urban)



Source: Own calculations using NIDS Dataset

In the analysis of wave 2 of the national incomes dynamics study data shown in figure 12, the marginal change in the comprehensive digital index was significantly higher for rural areas than for urban areas, indicating much higher access to smartphones than in urban areas. The marginal change in the mean index for communication assets was much smaller for rural areas while it fell slightly for urban areas. This showed very low access to other digital assets such as computers in rural areas, while the slight marginal decline in the index for urban areas might be attributable to an increase in communication assets ownership but at a lower marginal rate, it could also be attributable to attrition in the dataset for various reasons. Comparing the various measures of digital access across spatial geographies shows the component of increased access to digital technology in rural areas to be access to digital phones which has been reported in several studies (Conradie D.P., Morris C., and Jacobs S.J., 2003; Diga, Nwaiwu and Plantinga, 2013; Adera, Waema and May, 2014; Lembani *et al.*, 2020; Jiyane, 2021).

Figure 13: Digital Index across spatial location, Wave 2



Source: Own calculations using NIDS dataset.

The decomposed mean of the comprehensive digital index considering population grouping showed some wide differences in the distribution of the mean albeit showing a higher index for rural areas than for urban areas. Taking spatial geography into consideration it can be seen that Africans had the highest mean (3.16), with the Indian population group having a second highest mean (4.14), the Coloured and White population grouping, (2.86) and (2.60) respectively. In the findings of the challenges of digital transformation in Chapter 6, it is stated that while there is noticeable digital integration, it is not that which participants can generate value except as they predominantly help build data streams as unpaid workers. This is characteristic of mobile-based digital technologies through applications that are accessible through smartphones and that are the medium through which the majority are experiencing the effects of technologies driving digital transformation (Abolhassan, 2017; Osmundsen, Iden and Bygstad, 2018).

Table 9:Decomposition of the mean of the comprehensive digital index across spatial location by population group.

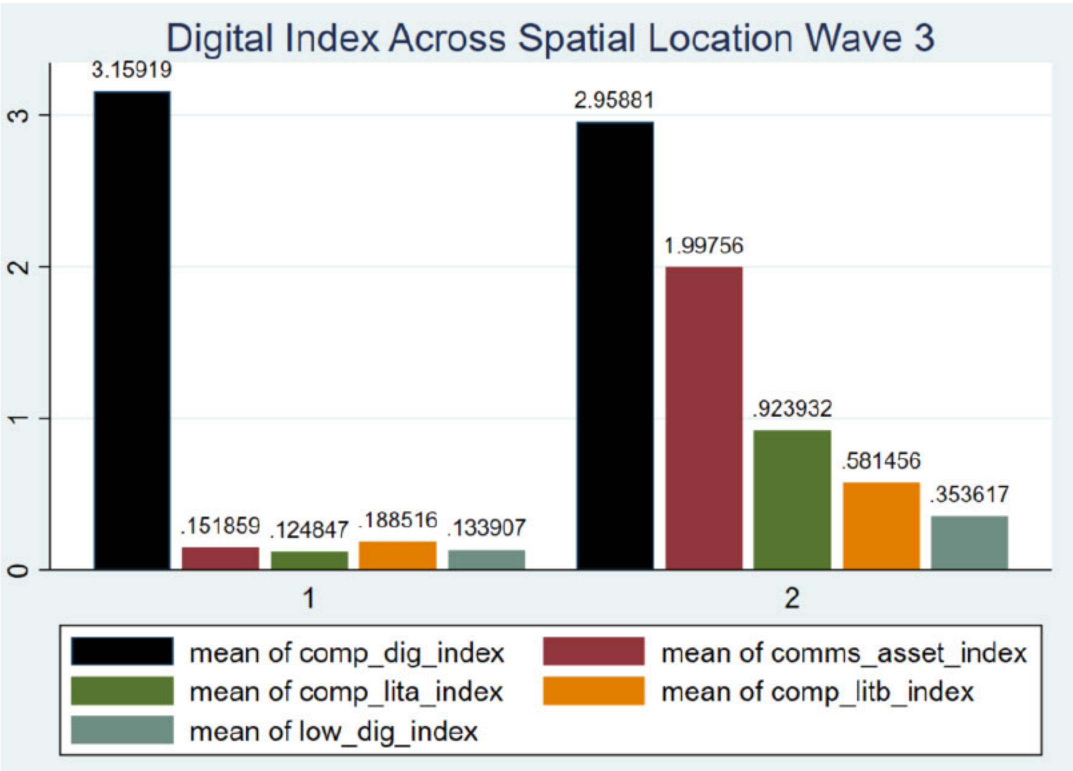
```
Survey: Mean estimation

Number of strata =        52        Number of obs    =        5,769
Number of PSUs   =     5,769        Population size  =   14,839,075
                                    Subpop. no. obs  =        2,718
                                    Subpop. size     =  5,227,822.8
                                    Design df        =        5,717

            1: population_grp = 1
            2: population_grp = 2
            3: population_grp = 3
            4: population_grp = 4
```

Over	Mean	Linearized Std. Err.	[95% Conf.	Interval]
comp_dig_index				
1	3.15728	.0241987	3.109842	3.204719
2	2.8563	.1193247	2.622378	3.090222
3	4.142244	.2202436	3.710483	4.574005
4	2.601518	.2693429	2.073504	3.129532

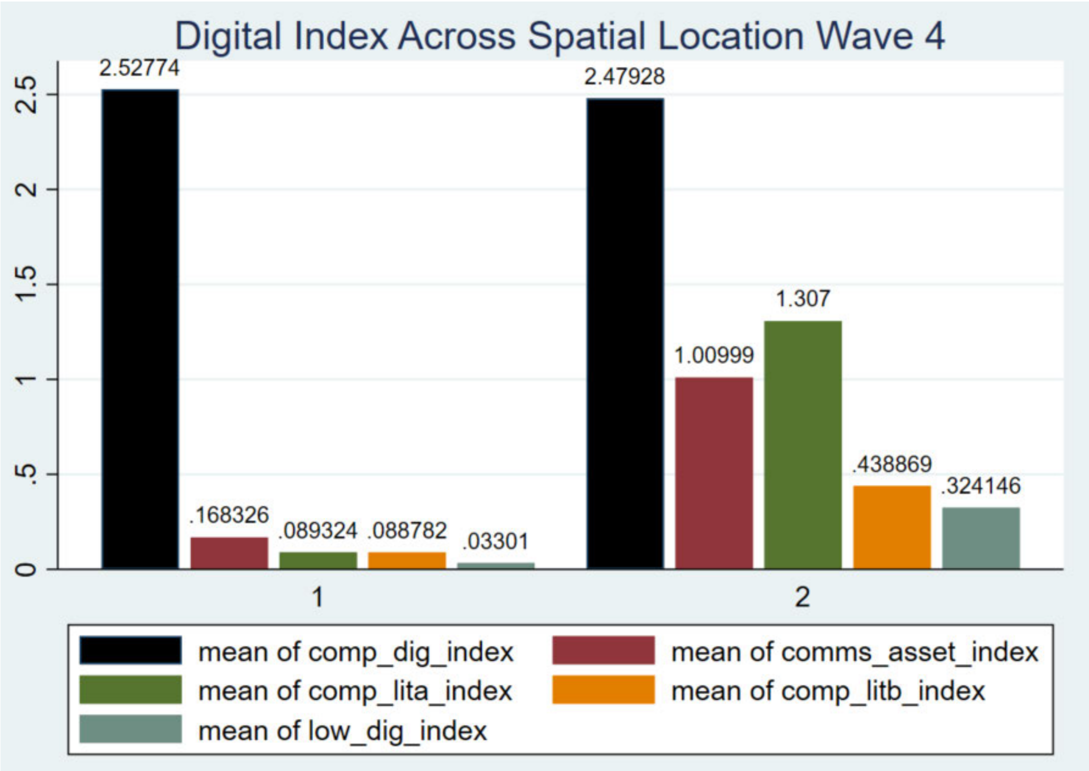
Figure 14: Digital Index Across spatial location, Wave 3



Source: Own calculations using NIDS dataset.

In the analysis of wave 3 of the data as presented in figure 14, the marginal change in the mean index for the comprehensive digital asset remained higher for rural areas, although the marginal change in the mean index for urban areas showed a significant rise. The marginal changes in the communication asset index, computer literacy and low digital index have remained higher for urban areas and significantly lower for rural areas. Thus, there is a very strong digital divide between rural and urban geographies and defined for higher-level digital skills, such as access to productive computing and digital skills.

Figure 15: Digital Index Across Spatial Location, Wave 4

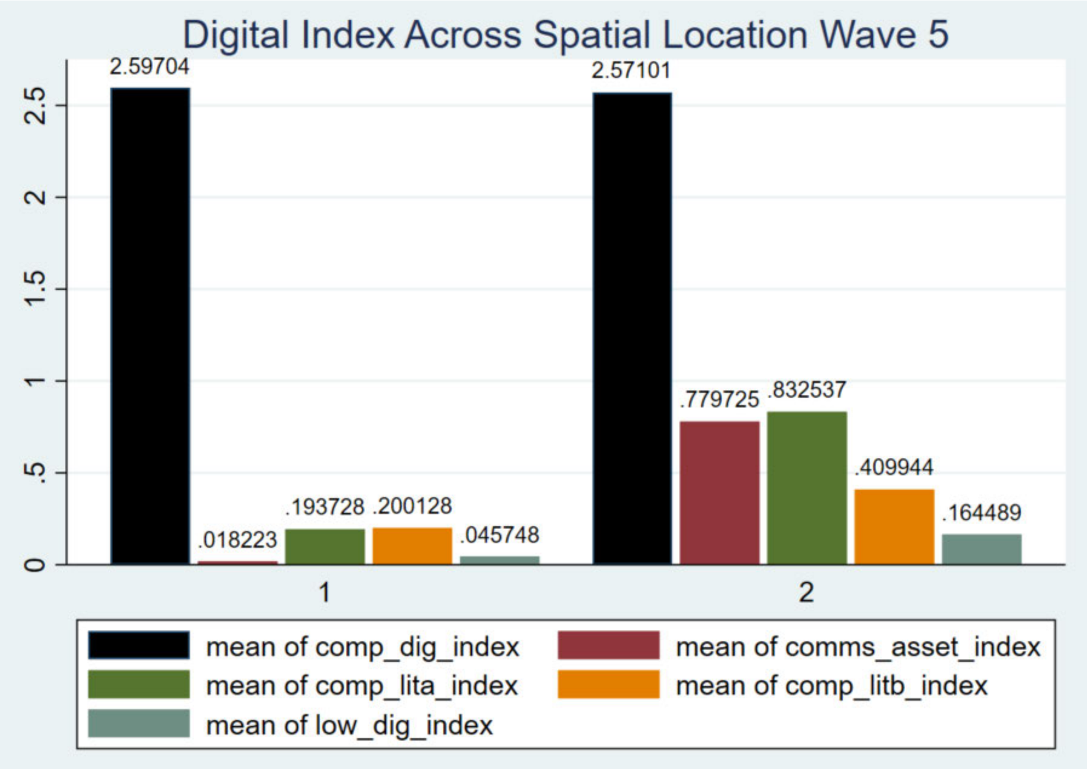


Source: Own calculations using NIDS dataset.

In the analysis of the digital divide in waves 4 and 5 of the data, shown in Figures 15 and 16 respectively, it is demonstrated that the digital divide remained in these subsequent waves of the national incomes' dynamics study data. The mean index of the comprehensive digital asset relatively equalized for rural and urban areas, as reiterated earlier that ownership of a cell phone was the highest loading in this index, the equalisation reflects that there has been a reduction of the divide in terms of mobile device ownership, although with no improvement in stock of digital skills such as basic or advanced computing skills that have to do with technology development, particularly for rural areas. The marginal changes in each respective spatial geography have become smaller, such that apart from the comprehensive digital index, the rest are less than 1, while for rural areas marginal change in indexes for communication assets, computer literacy and low digital index is not significantly different from zero in both waves 4 and 5 of the data. The mean indexes for advanced computer skills, basic computer skills, communication asset index and the low digital asset index for the urban geographical segment though higher than for rural geographies are nevertheless below 1.

A comparison of the digital divide based on spatial considerations from wave 1 to wave 5 of the national incomes' dynamics study, shows that the marginal change in the mean indexes for the urban geography has been constantly declining particularly for the communication asset index, advanced computer skills, basic computer skills and low digital index. This reflects the change in the composition of the indexes, from aspects such as telephone ownership, digital satellites, towards higher weights on computers, digital skills, internet/broadband access and working telephones. It also shows that the stock of digital skills has been changing at a very low marginal index, and when the spatial factor is integrated at the observed rates, the digital divide is likely to remain in the unforeseeable future. The analysis thus shows that mobile device access has remained steady, however, more advanced digital technologies and skills are still in very short supply.

Figure 16: Digital Asset Index across Spatial Location, Wave 5



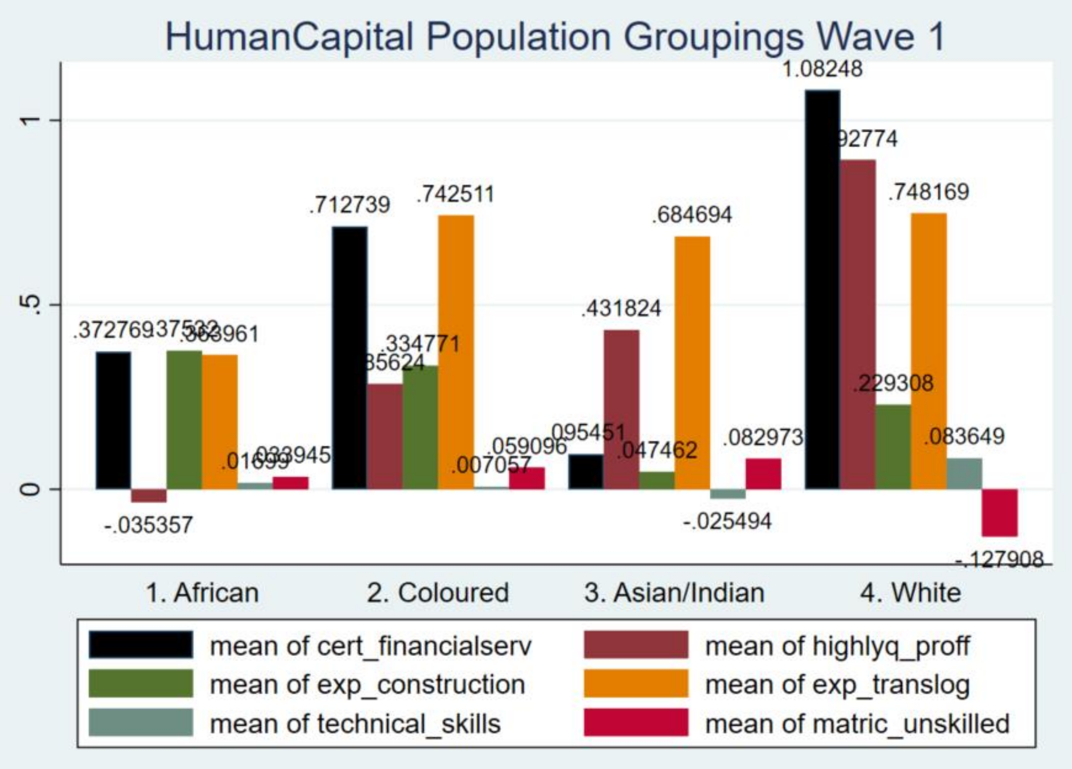
Source: Own calculations using NIDS dataset.

5.6. Human Capital Index across population groupings

In assessing the human capital index, attention was paid to sub-indexes relating to jobs where either high-end competency is required, such as innovation, creativity and problem solving or that incorporated use of digital technologies in the task processes. From a total of 19 sub-indexes measuring different aspects of human capital, only 4 are reported for space considerations using the parametric mean on bar charts. These reported are financial skills, professional skills, transport and logistics and construction industry skills.

In the analysis of wave 1 of the national income dynamics study shown in figure 17 below, mean human capital indexes of workers in the financial services, the professional services, construction, transport and logistics, technical sector and the unskilled workers across the population groups were assessed. The White population group had the highest mean index for financial service skills, professional skills and the transport and logistics sector. The Asian/Indian population group had the second highest mean index for professional services, followed by the Coloureds and then the Africans. Overall representation among the groups was also considered since the African population group comprises the largest demographic proportion among population groups in South Africa. The Africans had a negative mean index for highly qualified professionals, while Asians/Indians had a negative mean index for experienced construction work and the Whites had a negative mean index for unskilled workers. The analysis showed based on the distribution of work within these sectors that African, Coloured and Indian population groups were less represented in the sectors of work where work required some level of digital skills and highly represented in sectors with less reliance on digital skills, such as low skilled construction work, low skilled transport and logistics, unskilled work with very low stocks of technical skills.

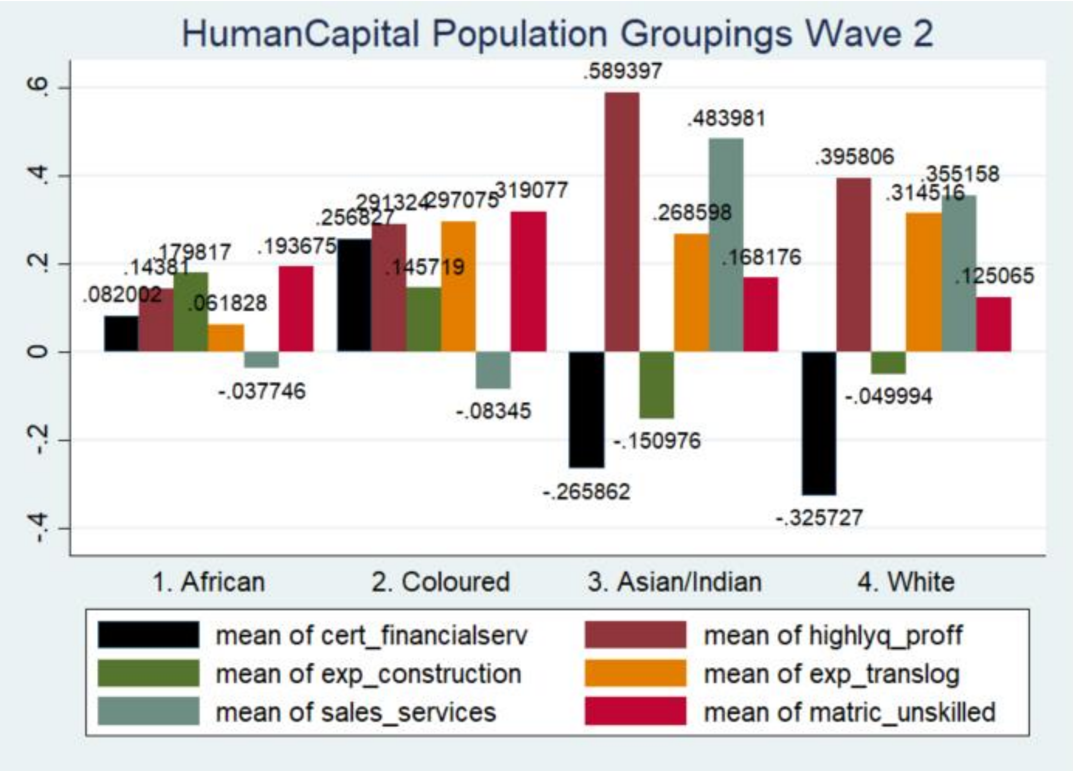
Figure 17: Human capital across population groupings, Wave 1



Source: Own calculations using NIDS Dataset.

In the analysis of wave 2 of the data presented in figure 18 below, the marginal change in the human capital indexes showed both positive and negative changes. The number of Africans with financial service skills has continued to increase but at a very low marginal index when compared to its level in wave 1, and so is the marginal index of financial service skills among Coloureds. The analysis shows a decrease in the number of Whites and Asians/Indians in financial services as shown by the negative marginal indexes, -0.33 and -0.27 respectively. It is also noticed that the African and Coloured population groups continued to gain marginally in the construction sector as shown by the small positive marginal index for experienced construction, while the Asian/India and White population groups showed a marginal decline as shown by the negative marginal indexes. However, concerning highly qualified professionals, Asian/Indian and White populations continued to show significant marginal gains as shown by the slightly larger positive marginal indexes, as well as for marketing and sales and the transport and logistics sectors. The negative marginal index for marketing and sales skills for African and Coloured population groups shows the categorisation of the marginal change in skills since the focus of the measurement was on high-end marketing work, which according to statistics in figure 18 is highly dominated by Asian/Indian and Whites during this period. The negative indexes thus showed a different category of marketing and sales skills, the lower-skilled category, meaning Africans and Coloureds were concentrated in the lower-skilled marketing and sales sectors. Thus overall, the divide in the distribution of skills is noticeable, with Africans and Coloured dominating the lower end of the skills and low skilled sectors while White and Asian/Indian population groups dominating high-end skills sectors and work.

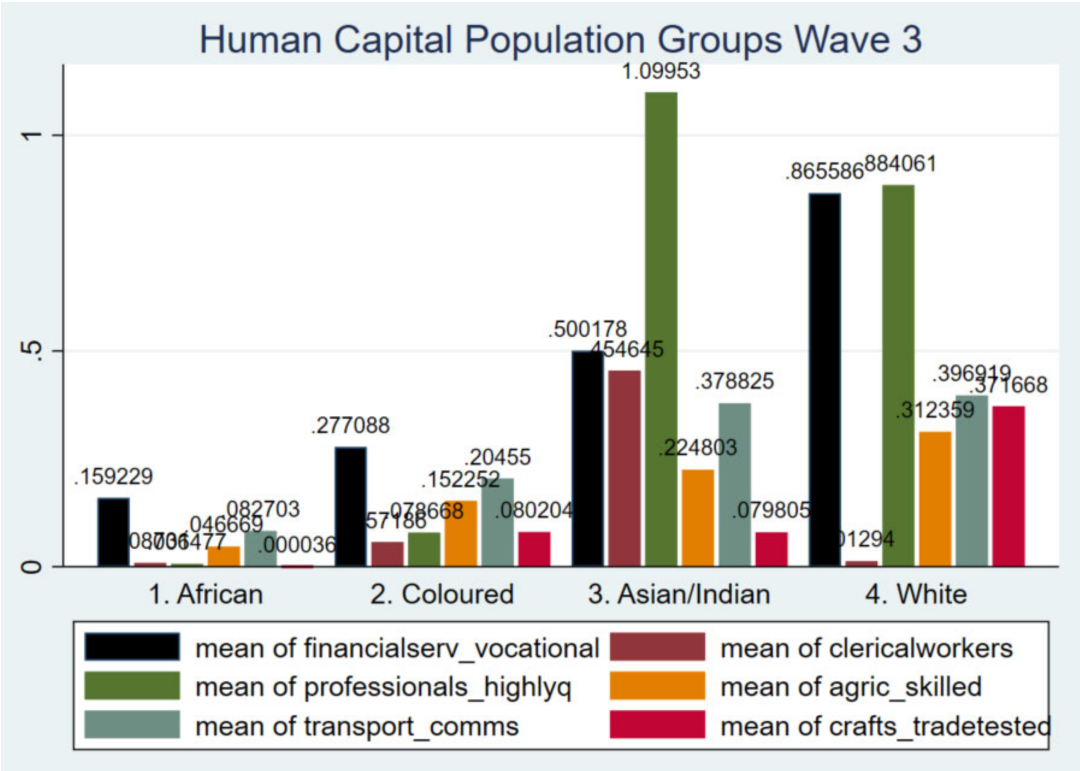
Figure 18: Human Capital across Population Groups Wave 2.



Source: Own calculations using NIDS dataset.

In the analysis conducted on wave 3 of the data and presented in figure 19, there was a shift in considering skills gained through vocational training or in-work-training programs, so vocational training based financial skills, crafts and technical trade tested skills and agricultural skills were included with the rest of the skills that have been the subject of analysis from wave 1. The marginal change in access to such skills as shown by the mean index, for vocational financial skills, agriculture skills and trade tested crafts and technical skills, is higher for Whites and Asian/Indians respectively. This might indicate that these population groups have been garnering work experience and vocational and in-work training, while Africans and Coloureds were pursuing conventional training such as a college degree. The marginal change in the mean index for Africans and Coloureds for technical crafts, skilled agriculture and vocational based financial skills is very low, which might indicate very few from these groups gaining skills through this alternative route. The Whites and Asians/Indians have continued to show higher gains in professional skills, transport and logistics with Asians/Indians showing a higher marginal gain in the mean index for clerical and administrative skills. Innovation and experience are associated with work-based training and technical skills, which the Whites and Asians/Indians feature prominently. The White population group has the highest mean index in crafts and trade tested skills which are highly associated with entrepreneurial direction and small business development (SEIFSA, 2018[1]).

Figure 19: Human Capital across Population Groups, Wave 3.



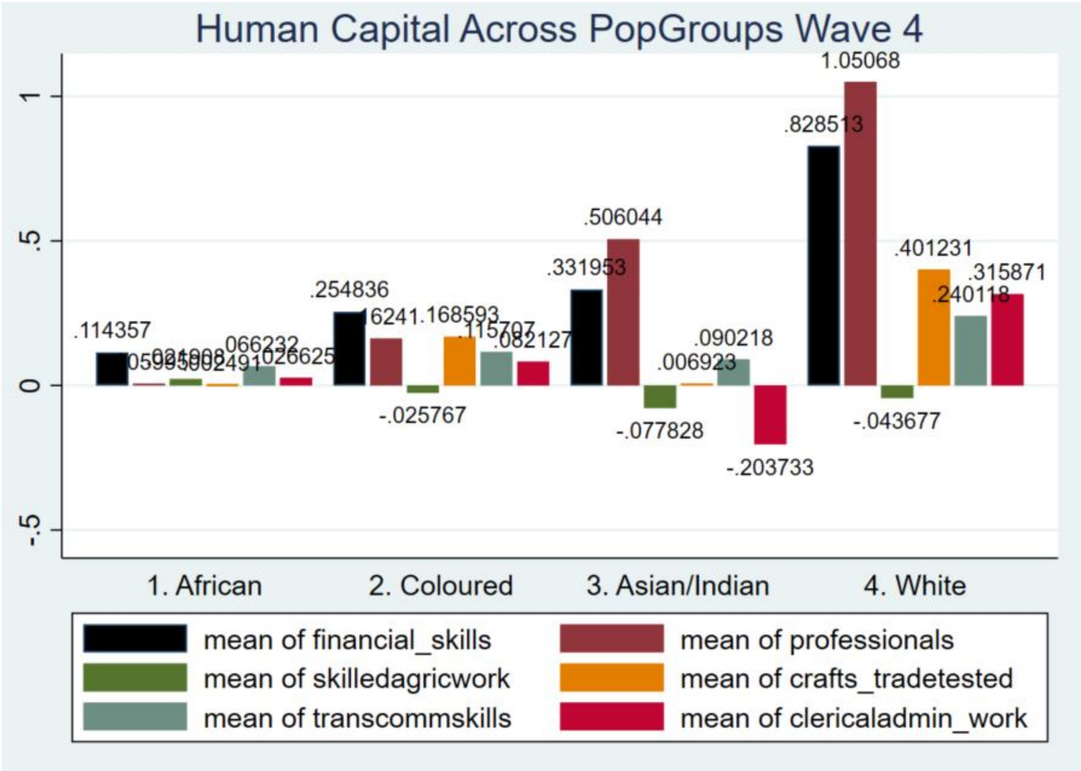
Source: Own calculations using NIDS dataset.

The analysis of wave 4 of the data presented in figure 20, continued to show a higher marginal change in stocks of financial and professional skills for the White and Asian/Indian population groups. The same groups also continued to show a higher marginal index in crafts and technical skills, with the Whites having a higher marginal index of transport and logistics although the marginal index is at a lower level than in previous waves of the data. The analysis also showed a negative marginal index in skilled agricultural skills for Whites (-0.044), Asians/Indians (-0.078) and Coloureds (-0.026), while there was a small positive marginal gain for Africans (0.002). Overall, what can be observed is the continued skills divide giving advantage to the White and Asian/Indian population groups. The high marginal indexes for technical and work-based skills are very significant when considered that they provide a perspective on the

[1] SEIFSA, online article, South Africa needs a strong technical skills base to grow the economy, South Africa needs a strong technical skills base to grow the economy – SEIFSA Training Centre

structure of the South African economy, where the White and Asian/Indian population groups control a significant share of the business and entrepreneurial activity (SEIFSA, 2018).

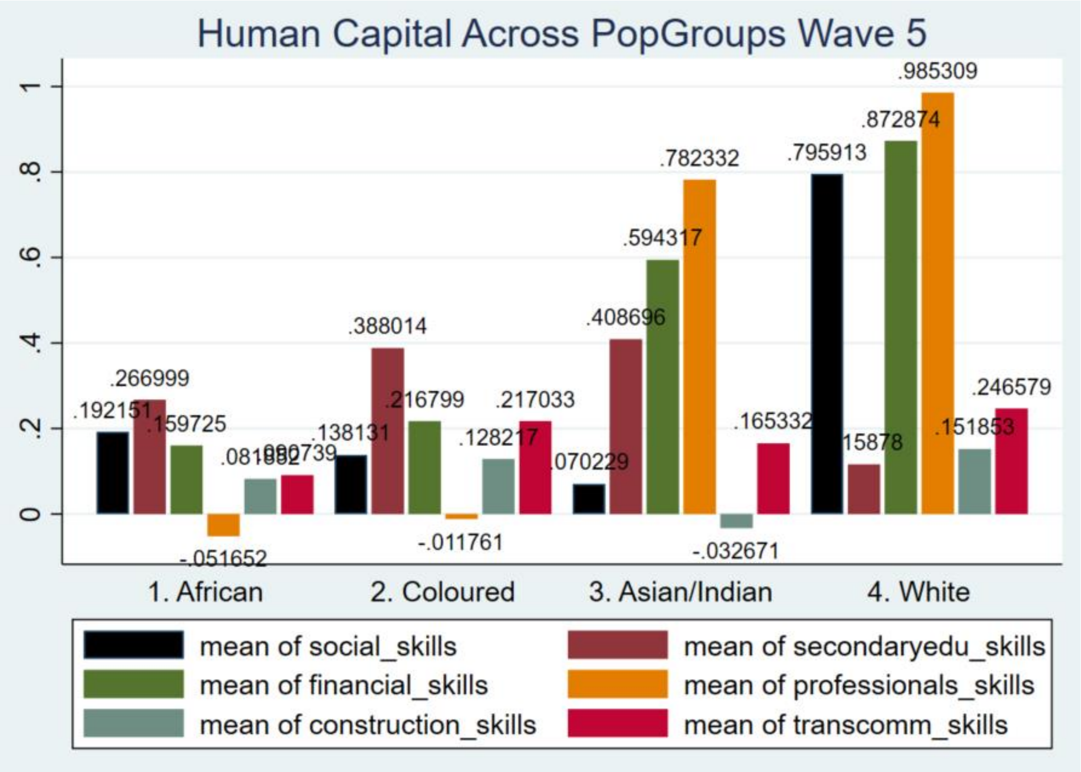
Figure 20: Human Capital Across Population Groups, Wave 4



Source: Own calculation using NIDS dataset

These findings are significant since these differences in skills endowments have been described in other studies as the demographic profile of skills that have resulted in the pattern of entrepreneurial development in South Africa. The skills endowments among potential entrepreneurs, the alignment of the skills with the sectoral dynamic changes are the critical factors that have been given as contributing to the success or failure of entrepreneurial endeavours in south Africa (Ligthelm, 2008; Farrington, Venter and Louw, 2012). In an earlier study, the skills profile observed in these findings is aligned with the problem of structural unemployment in South Africa (Madhou and Sewak, 2019).

Figure 21: Human Capital Across Population Groupings Wave 5



Source: Own calculations using NIDS dataset.

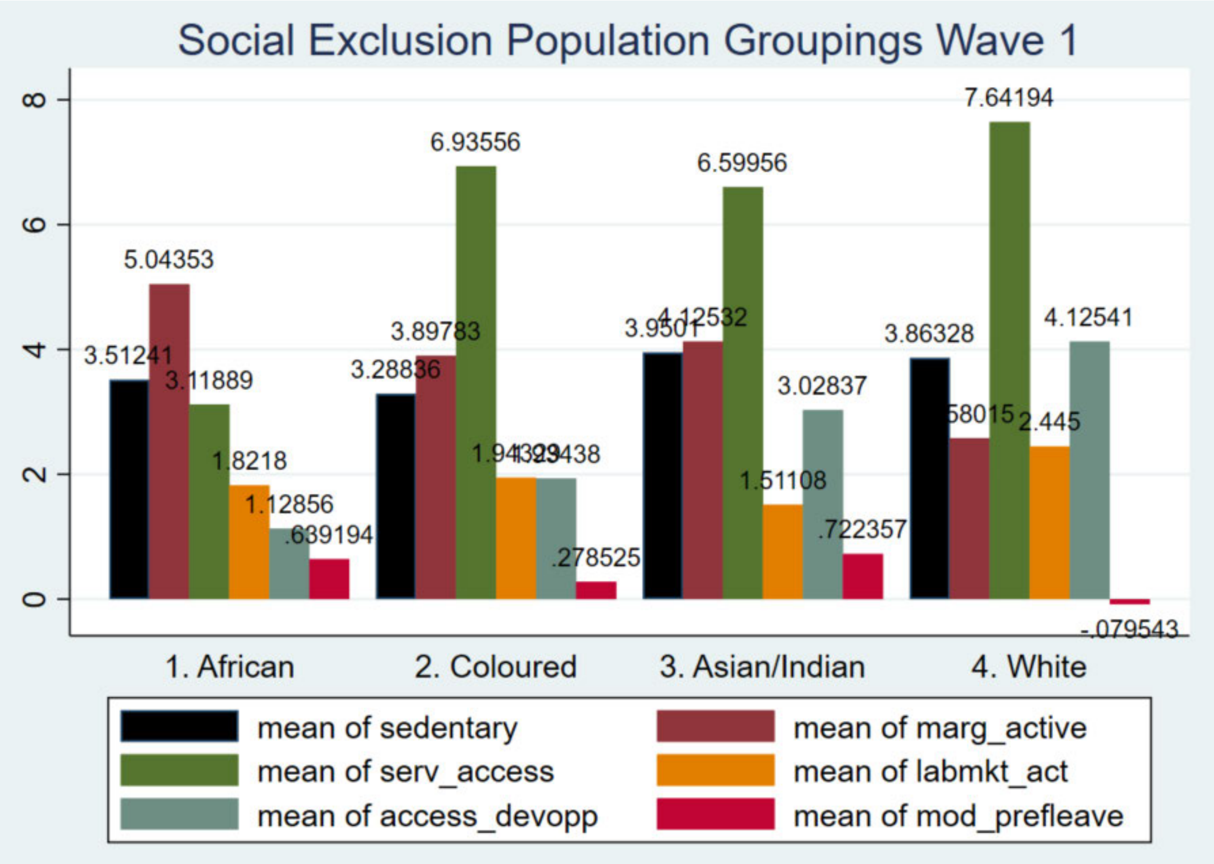
The analysis of wave 5 of the data presented in figure 21 above, showed that the marginal indexes for Whites and Asians/Indians in professional skills, financial skills and transport and logistics remained high. An index assessing social skills was also included and the low skills measure was included to measure the presence of very low levels of skills. The White population group showed a higher mean index for social or collaborative skills, the highest mean index for financial service skills and the highest mean index for professional skills followed closely by the Asian/Indian population group as shown in figure 21. The White population group continued to have the highest mean index in transport and communication skills, followed by the Coloured and the Asian/Indian population groups. Africans have a negative index for professional skills, they demonstrate lower-end professional skills. There is a resilient divide in high-end skills across population groups, which according to some research publications (SEIFSA, 2018; Litheko *et al.*, 2019), explains the entrepreneurial structure of the South African economy and the consequent income distribution. However, it is noticed that the categories of work or skills where the African population group were trailing, were also the categories of work or skills that determine the entrepreneurial capacity of the economy. There is thus a need to promote either the use of high-end skills or the development thereof, such as collaboration, communication skills, and supply chain planning as in transport and communication/logistics and professional skills among others.

5.7. Assessing social exclusion

The creation of the index for social exclusion which was designed as explained in the preceding chapter to measure the individual or household capacity to pursue personal development opportunities, through access to services and institutions, produced 23 components/variables. The variables measured some aspects of social exclusion grouped under the variable in the component with the highest loading. Among the 23 components, 5 were selected as having relevance to the present analysis and these measured, marginal economic activity, access to services, strong preference to stay in a given area, labour market access, access to developmental opportunities and access to institutions of higher learning. These were assessed across population groups with the mean index as its distribution and marginal change as the statistic of interest.

Figure 22 is a presentation of the findings of the analysis of wave 1 of the national income dynamics study data. The mean index for access to services across the four population groupings highlights the divide in service access. The White population group has the highest mean index (7.64), with the Coloured population group having the second-highest mean index (6.94), the Indian population group (6.60) and the African population group (3.12). The African population group has the lowest mean index for access to developmental opportunities, in terms of institutional access, and other personal developmental services. Access to developmental opportunities index, included access to credit, educational development opportunities, life insurance and medical aid, a higher index showing better access to these services and institutions. In an environment characterised by the expectation of imminent pervasive transformation and learning opportunities being key to adaptation to uncertainty and change, access to developmental opportunities is critically important (Sousa and Rocha, 2019). Combined with low access to developmental opportunities, the African population group had the highest index for marginal economic participation (5.04), measured by broader economic participation such as labour market participation, business ownership or other forms of economic activity. The index of labour market participation for the African population group is lower than for the White and Coloured population groups but higher when compared with the Asian/Indian population group. Labour market participation is influenced by access to and holding of skills, with the labour market being the central institution for both economic participation and income distribution, with a low labour market participation index indicating social exclusion. The large mean index statistic for economic marginalisation shows the extent to which the African population group has been largely excluded from the economic institutions. A study indicated that capital concentration exacerbates the immiseration of socially excluded groups and also decreases the wages or returns of socially excluded groups. The combination of these factors shows that social exclusion contributes to increased income inequality (Hazari and Mohan, 2015). The decomposition of social exclusion in these findings also aligns with the understanding of social exclusion as conceptualised in literature as determining levels of participation (Taket *et al.*, 2009).

Figure 22: Social Exclusion Analysis across population groupings Wave 1



Source: Own calculation using NIDS dataset.

The analysis using wave 2 of the dataset presented in figure 23, showed sharp changes from wave 1. Firstly, it can be observed that there was a sharp decline in the mean indices across the board, the marginal change remained high and positive sedentary, access to services and economic activity. The data in wave 2 corresponds with the post-2008 period of heightened unemployment and pathways towards economic recovery (Steytler and Powell, 2010). What is observed in figure 23, is a sharp negative development in social exclusion, particularly with indices measuring access to developmental opportunities, marginal economic participation and labour market participation. Labour market participation declined across all population groups from mean indices of African (1.13), Coloured (1.95), Asian/Indian (1.51) and White (2.45), to African (0.44), Coloured (0.11), Asian/Indian (-0.06) and White (0.16). According to the quoted paper, this period was associated with increased joblessness, slow recovery and decline in public revenue as against increased demand for social assistance (Steytler and Powell, 2010). White and Indian population groups showed an increased preference to relocate when comparing the mean for preference to leave in figure 22 and 23, the mean index for the White population group doubled, while the negative marginal change on Asian/Indians was significant inclining towards a greater preference to relocate from the recorded spatial location. Sedentary individuals and households were associated with characteristics of strong spatial immobility, average income and being economically inactive, with characteristically strong mean indexes in both wave 1 and wave 2. A rudimentary assessment of sedentary across spatial geography shows that the mean index was higher in the rural areas than in the urban areas, for nearly 14 million South Africans as shown in table 7 below. The majority are thus, rural households headed by elderly individuals who are economically inactive, on average income and immobile.

Table 10: Tabulation of the mean index of sedentary across spatial geography (1=Rural, 2=Urban)

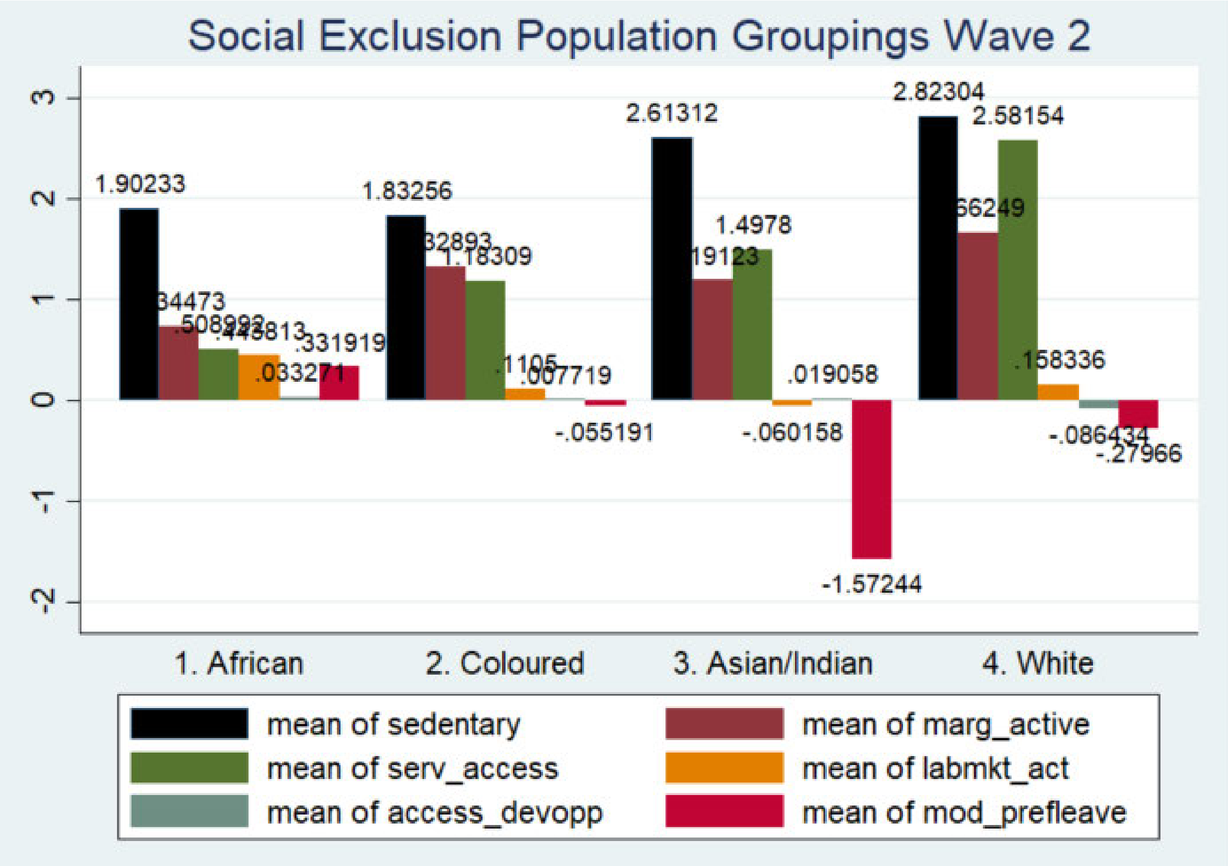
```
Survey: Mean estimation

Number of strata =  53                  Number of obs   =      7,296
Number of PSUs   = 401                  Population size = 13,972,673
                                        Design df       =        348
```

	Mean	Linearized std. err.	[95% conf. interval]	
c.sedentary@spatial				
1	3.759594	.0579083	3.645699	3.873488
2	3.441408	.0594781	3.324426	3.558389

Source: Own calculations using NIDS dataset.

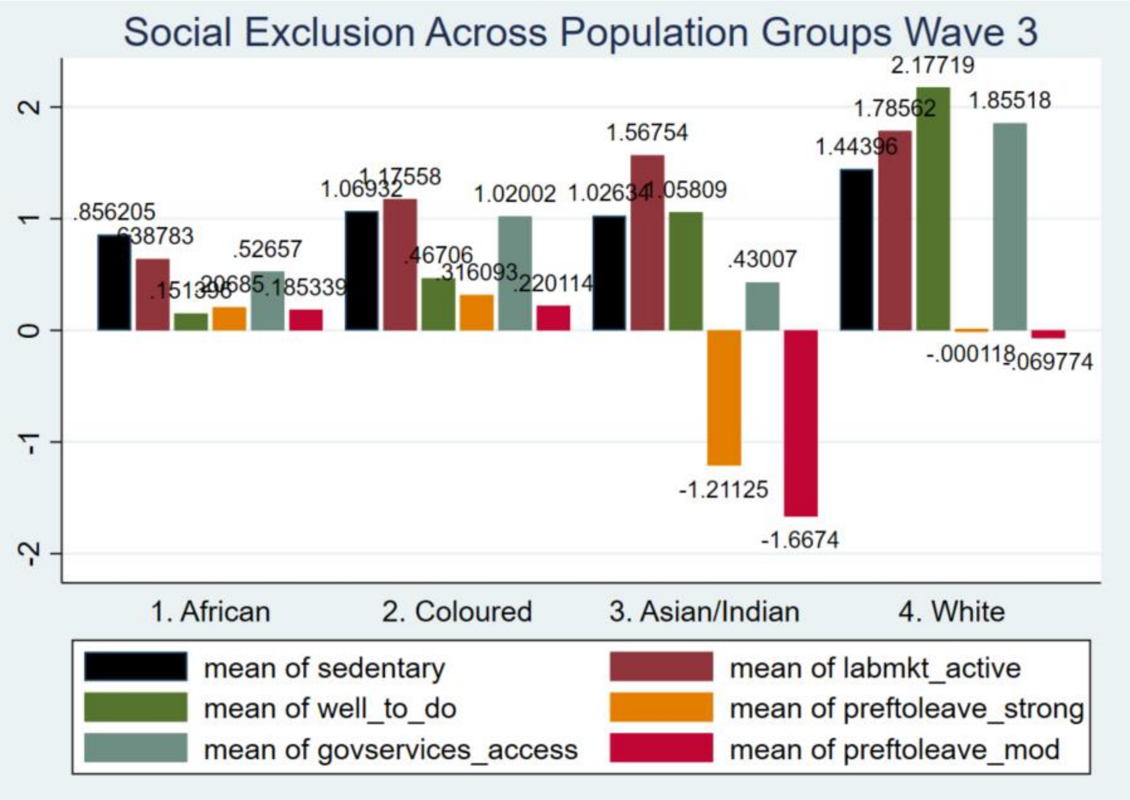
Figure 23: Social Exclusion across population grouping Wave 2



Source: Own calculations using NIDS Dataset.

The analysis of the sub-indexes of the social exclusion index showed that the mean index for preference to stay in the present geographical location assessed in Wave 1 (2008), had declined among Africans. The population group however had become active in the economy (showing the lowest index for marginal economic activity), retained the lowest mean index for access to services and while the mean index for labour market participation fell across all population groups, Africans still retained a high index when compared to others (this might be explained by affirmative action policies such as BBBEE, or simply that Africans are over-represented in the population). The mean index for access to developmental opportunities declined across all population groups, however, the African population group retained a slightly higher mean index when compared to Coloured and Indian population groups, while the White population group showed a large negative value. This slightly larger marginal index change shows that around this time, most Africans obtained debt finance, increased educational investment and other services such as life insurance policies and medical insurance, which factors are associated with a developing middle-income class. This sub-index was influenced by high loadings in variables measuring life insurance, access to clean water, vehicle ownership and internet facilities among other variables with high loadings, and these were made possible in part by affirmative policies which saw increased economic participation, labour market participation and black middle-class development (Burger and Jafta, 2010; Harper and Griffin, 2010). This fact also explains the positive gains indicated by the small mean for middle-income class households' access to university education when compared to the same analysis in wave 1 above. The negative mean index for the White population group could be indicative of the massive shift in access to university weighted by the population subgroup (middle income demography) which became populated with African households as against other population groups during this period (Harper and Griffin, 2010).

Figure 24: Social Exclusion Analysis across Population Groups, Wave 3.



Source: Own calculations using NIDS data.

The analysis of wave 3 of the data presented in figure 24, showed a marginal decline in the mean index of sedentary particularly among the African population group, with the spatial analysis showing a shift in the spatial distribution of the index from rural towards urban areas, across nearly 15.4 million South African households (Table 8). The mean index for access to government services is higher for Whites and Coloureds and lower for Africans and Indians significantly, which showed greater access to government-provided services and infrastructure, a divide in service access. The measurement of this variable included a wide range of government level services from street lighting, subsidies, refuse services and water services, which reveals the existing physical divide in access to services. The variable measuring access to developmental opportunities was assessed as *well to do,* measuring access to credit lines, educational development, bank-financed assets, life insurance and medical aid, which shows heightened differences, particularly between White (2.18) and African (0.15). This marginal change, significantly higher for Whites and Asians/Indians than for Africans and Coloured showed that at the time of the survey, the former had increased access to developmental opportunities than the latter group.

Table 11: Tabulation of the mean of sedentary across spatial geography for in wave 3 data for comparison with wave 1 (1=Rural, 2=Urban)

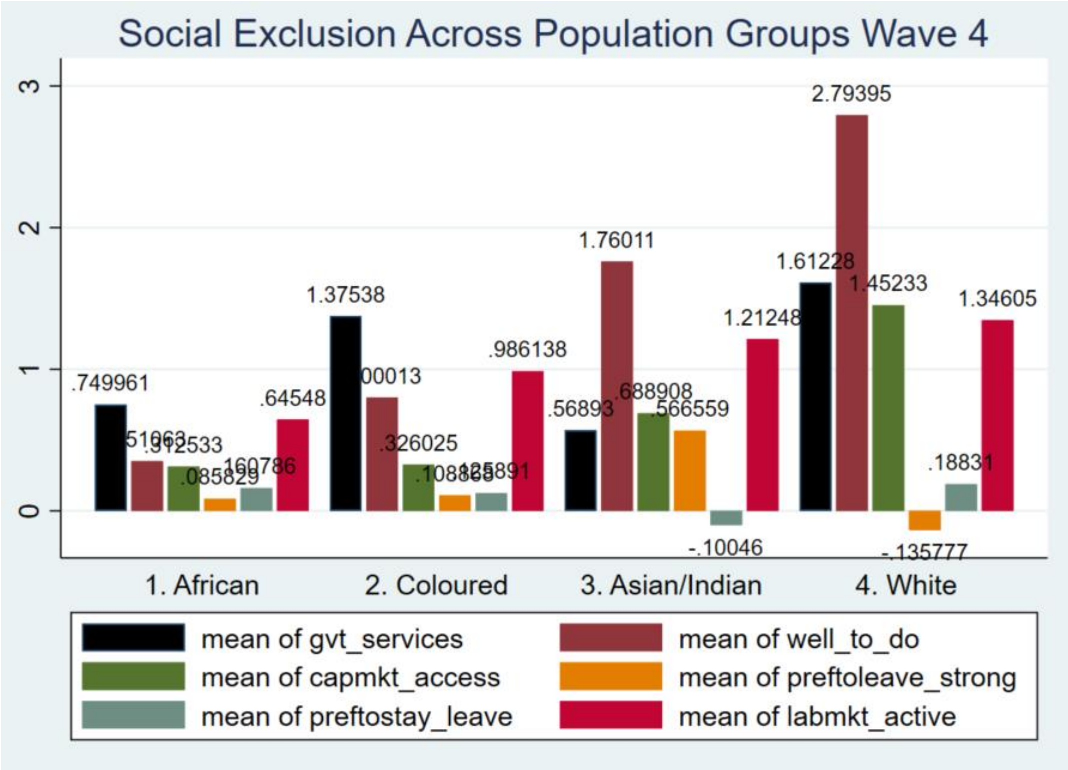
Number of strata =	53	Number of obs =	5,895
Number of PSUs =	5,895	Population size =	15,481,571
		Design df =	5,842

1: spatial = 1
2: spatial = 2

Over	Mean	Linearized Std. Err.	[95% Conf.	Interval]
sedentary				
1	.9435395	.0429055	.8594287	1.02765
2	1.150529	.0420374	1.06812	1.232938

Source: Own calculations using NIDS data.

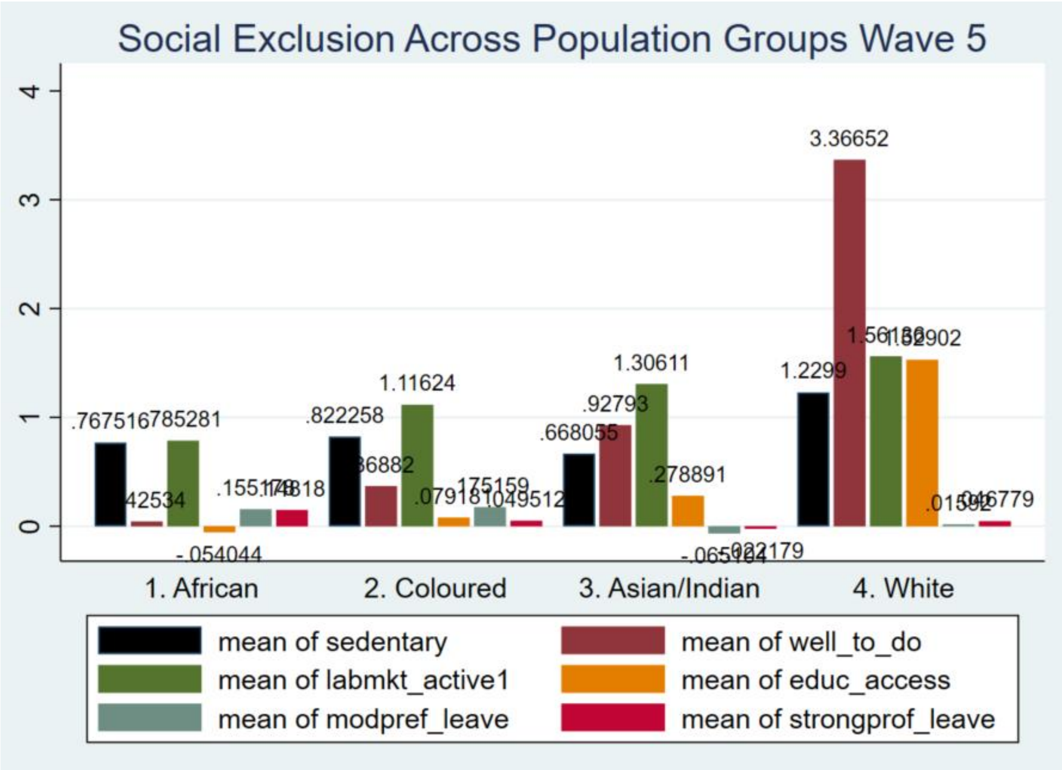
Figure 25: Social Exclusion Analysis across Population Groups, Wave 4.



The analysis using wave 4 of the data presented in figure 25 shows increased differences in the marginal change indicated by the mean index for access to developmental opportunities particularly among Africans (0.52) and Whites (2.79), the latter showed greater access to developmental opportunities than the former. The Africans had the lowest marginal change in labour market participation, capital market access and still lower marginal index for government access provided services. Thus, the physical divide persists in inequalities in access to services, developmental opportunities, institutions and livelihood possibilities, as shown in figure 25 above.

The analysis for wave 5 of the data presented in figure 26 shows an increasing divide in access to developmental opportunities, educational institutional access and labour market access, distributed across population groups. There is a significant marginal increase in access to developmental opportunities among Whites (3.37) when compared with Africans with a declining mean index (0.04). Since, social exclusion was measured as access to opportunities for participation in institutions, upgrading and economic participation, the physical divide, has been resilient across the waves of the data skewed against Africans, Coloured, Asian/Indian and Whites in that order. Throughout the 5 waves of the national income dynamics study, analysis of social exclusion in terms of institutional access, access to infrastructure services and developmental opportunities is resiliently skewed across population groups, which might give a picture of the structure of adaptation possibilities in the face of digital transformation, as those who experience social exclusion presently are more likely to be excluded particularly when the institutions change and their skills are rendered of no use by the transformation.

Figure 26: Social Exclusion Analysis Across Population Groups, Wave 5

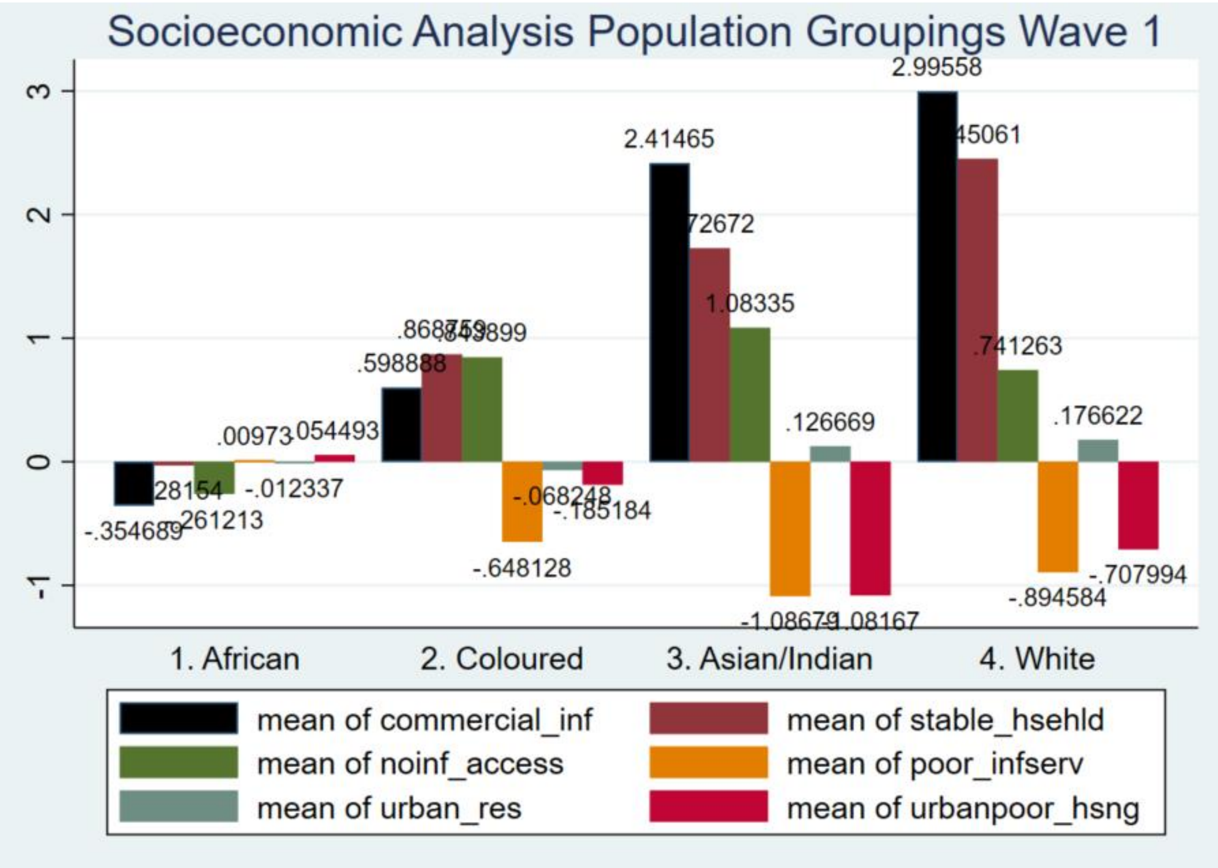


Source: Own calculations using NIDS dataset.

5.8. Socioeconomic Index assessment

In creating the variable for socioeconomic status, 50 components measuring different aspects of socioeconomic welfare across the population groupings were generated, resulting in 50 sub-indexes and as outlined in the research methodology (section 4.6.2.1), there was no attempt to coalesce all of the sub-groups into a single index, however, recourse was to generate indexes commensurate with the aggregate number of components. In the analysis, 6 variables were created from 6 selected sub-indexes, measuring aspects of socioeconomic status related to socioeconomic welfare maintenance potential of individuals and households. The six variables selected were measures of socioeconomic stability, access to household level services, access to infrastructure such as housing, wealth, access to resources and household size (as a proxy for per capita pressure on resources). Graphical representation has been used to report the findings of socioeconomic welfare analysis. The variables measuring socioeconomic status and social exclusion presented earlier look similar yet are different in their focus. The socioeconomic status variables are based on analysis of the internal dynamics of the households, in terms of assets, income and opportunities for making or improving their welfare, while the social exclusion variables examined the household's access to external facilities for development and economic mobility. Therefore, such metrics as access to institutions, credit facilities, spatial transition, economic participation and services were analysed to indicate whether households experience social exclusion or not, and the implication of such exclusion in the face of digital transformation.

Figure 27: Socioeconomic Welfare analysis Wave 1

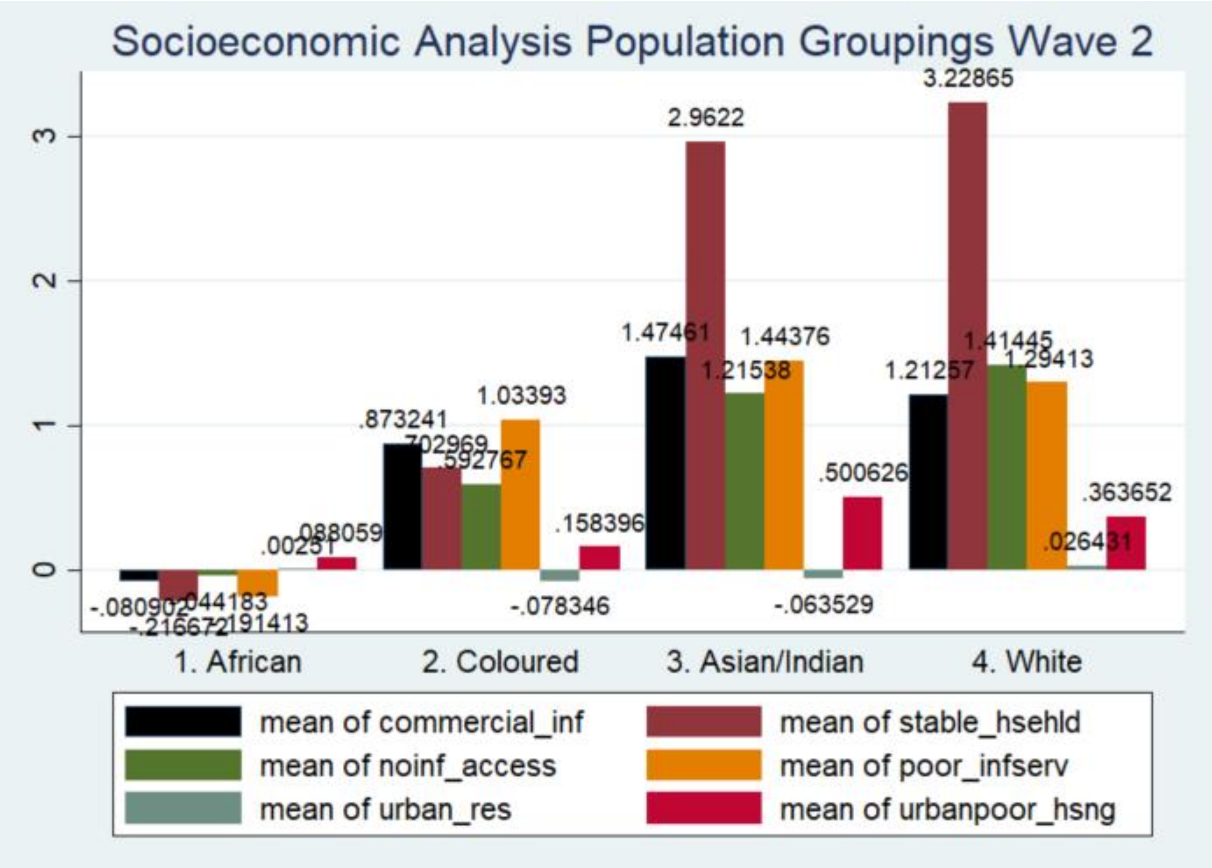


Source: Own calculations using NIDS dataset.

The analysis of wave 1 of the data presented in figure 27, showed that for the African population group, the mean index for access to productive infrastructure (commercial infrastructure = -0.35) was negative, and so were the mean indices of household stability (-0.028) and general infrastructure access (-0.26). The African population had the only positive mean index for urban poor housing. According to the findings of wave 1, the African population group demonstrated a general prevalence of poor socioeconomic conditions when contrasted with other groups, which has significantly larger mean indices for access to commercial infrastructure, household stability and general infrastructure services and large negative mean indices for poor infrastructure services and urban poor housing. This means that at the time of the survey, most African households were in poor income conditions, hence identified poor forms of housing, furthermore, the negative mean index on access to productive assets can be complemented by the poor access to credit facilities which was observed in the analysis of social exclusion.

The analysis of wave 2 of the data presented in figure 28, shows no improvement for the African population group in the mean indices for access for commercial infrastructure (-0.081), household stability (-0.22) and general service access (-0.19). The chart also shows Africans being a smaller share of residents of urban poor housing, having a small positive mean index of 0.088 when compared to Coloureds (0.158), Asians/Indians (0.50) and Whites (0.36). The negative mean index for socioeconomically stable households for the African population group worsened even though the marginal change is quite small, Coloured experienced a marginal loss in the same mean index while Indian and White population groups showed significant improvement in socioeconomic stability. Socioeconomic stability measured by the stable household index variable included attributes of secure housing, high income and higher education status, with the indexes showing deficiency of these in the African and Coloured population subgroups when compared with other population groupings. The other population groups had large positive mean indices for access to commercial infrastructure and household stability. These other population groups had large positive mean indices for general access to services (household services) and urban infrastructure services (streetlights, water and electricity) and in the computation of infrastructure services, the ability to pay as a proxy to access was factored in, with indexes reflecting it. It must be noted that the mean index of external infrastructure access, measured access to infrastructure services provided externally however important to the functioning of the household. The sub-index showed significant loadings of small household status, which explains the increase in access to low-income small housing across the African population group, and the shift towards middle income and high-income housing across the other population groupings. This shift has also been noted by other authors as being the result of policy, as well as increasing income across the African population group during this period (Litheko *et al*, 2019). However, the findings showed that the marginal effect of the change in socioeconomic fortunes for the African population group was not strong since the net effect remained negative, more Africans remained under conditions of poor socioeconomic conditions than those transitioning during this period.

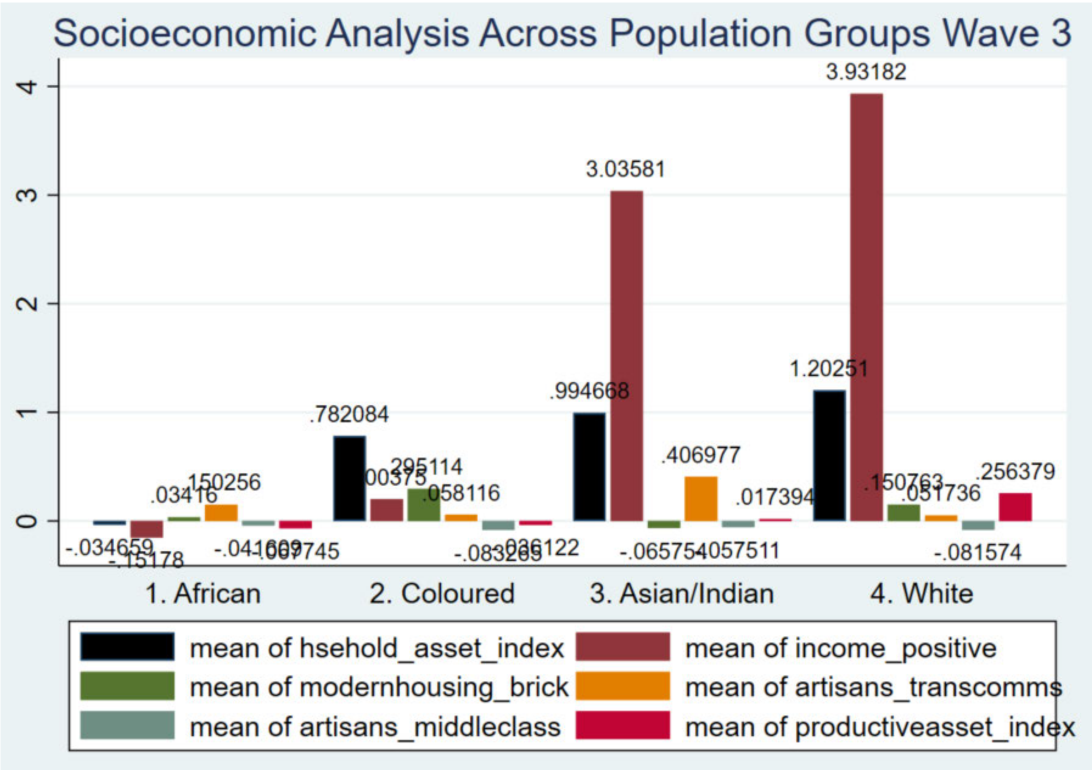
Figure 28: Socioeconomic variables findings Wave 2



Source: Own calculation using NIDS Dataset.

In the analysis of wave 3 of the data presented in figure 29, the household assets index was assessed instead of the household stability index, because of the loss of variables in the transition from wave 2 to wave 3. Other indices more or less remained the same. The marginal change in the mean for household asset index remained small and negative for Africans, with the negative mean index for positive household income (assessing income from multiple streams such as employment and commercial enterprises), and the marginal negative mean index for commercial infrastructure access (productive asset index). Thus generally, the African population group's socioeconomic circumstances did not improve in the assessment from wave 1 through wave 3. The analysis of the socioeconomic status of White and Asian/Indian population groups showed significantly large marginal mean indices for household assets and income as well as small positive marginal mean indexes for productive assets. This showed that these groups continued to gain in terms of household welfare and experienced significant positive gains in income and though at a smaller marginal change, they continued to experience gains in holdings of productive/commercial assets. The African population group had a negative mean index for middle income connected with technical work when compared to other population groups, which shows that Africans with technical skills had higher-end incomes as with other population groups, the mean indexes also showing the size of the representation during statistical computation, meaning that in addition to the small negative index, there were just a few Africans with high incomes and high technical abilities in the dataset.

Figure 29: Socioeconomic Analysis Across Population Groups, Wave 3

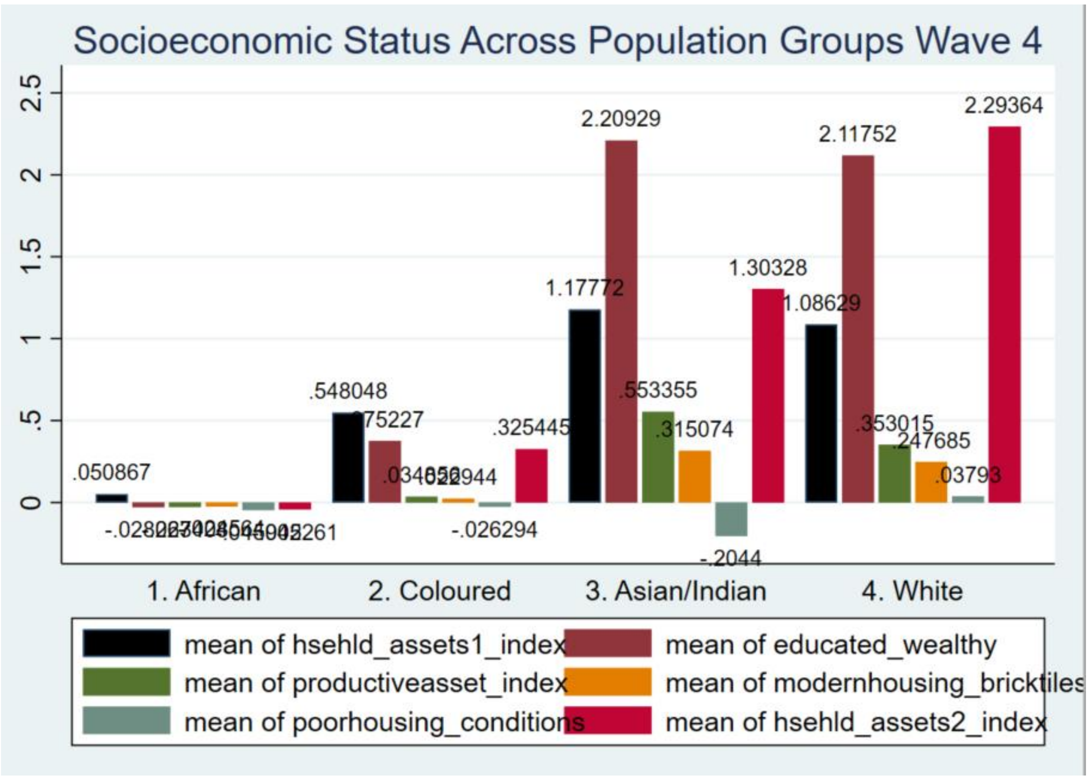


Source: Own calculations using NIDS data.

The analysis presented in figure 30 below shows findings of the analysis of socioeconomic welfare of households using wave 4 of the data continued to show a small and positive marginal mean index for access to household assets. The chart also showed that Africans had negative marginal mean indices for being educated and wealthy, access to productive assets, modern housing and housing conditions. The performance in terms of socioeconomic indices remained poor when compared to other population groups, particularly, for access to household level assets, wealth and education and access to modern housing. Poor access to productive assets, secure housing, education and wealth relegates individuals and households to lower access to developmental opportunities since these give a relative measure of household adaptability to changing social and economic circumstances.

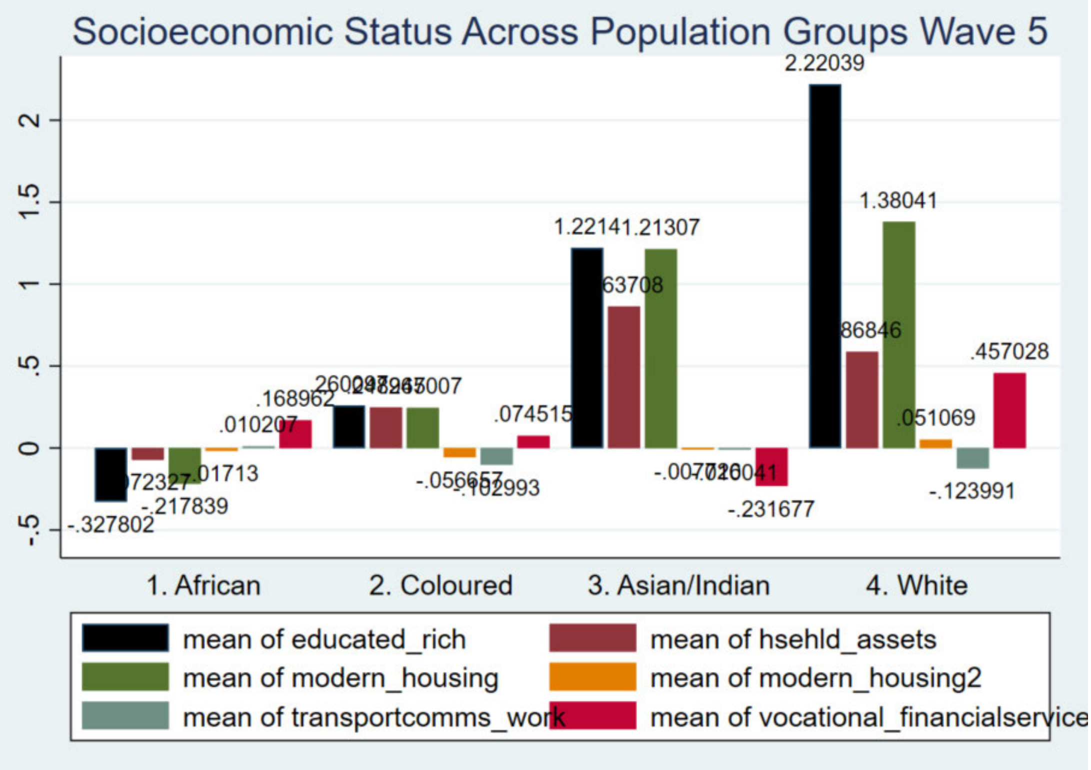
The analysis for wave 5 of the data presented in figure 31 below, shows somewhat of a continuation of the socioeconomic trajectory observed in the previous waves of the data. The African population group had negative mean indices for wealth and education, household assets and access to modern secure housing showing socio-economic deprivation. Poor access to services and ownership of assets reduces the coping capacity and resilience of a household in the face of pervasive social and economic change. On these three indices, the White and Asians/Indians showed better performance, with higher access to household assets, education and wealth and secure housing. The Coloureds while the marginal changes were lower still performed better on these indices than Africans. This is quite significant when it is considered that the analysis focused on at least 15 million households across South Africa, with the African population group representing at least 70 per cent of the households.

Figure 30: Socioeconomic Analysis Across Population Groups, Wave 4.



Source: own calculations using NIDS data

Figure 31: Socioeconomic Analysis Across Population Groups Wave 5



Source: Own calculations using NIDS dataset.

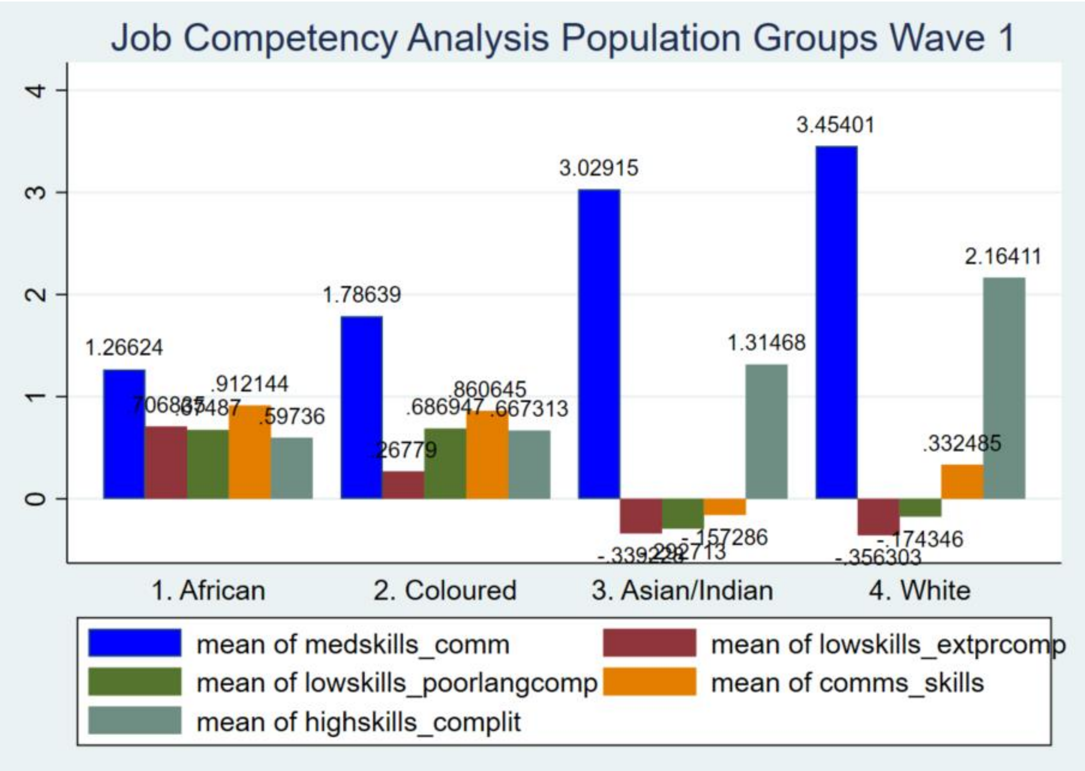
5.9. Digital transformation, social participation and income redistribution

The argument for socioeconomic welfare under DT is based on the contours of social and economic participation of individuals under new arrangements of social and economic activity. To do this, the individuals must be equipped to meet the demands of the new environment in terms of their skills and competencies, access to economic opportunities, upskilling and prospects for personal development. An analysis of the job and competency index, the upskilling index and the variables measuring access to personal developmental opportunities were assessed based on the population grouping variable for comparison purposes.

5.9.1. Job Competency index

This variable focuses on a range of skills that aligns with the perceived competencies in a digital work environment such as having computer skills, knowing how to use computers and other digital assets for productivity and ability to communicate in English, which presently is the standard language of communication in training, education, work and across platforms. The job competency index is broken down into 4 separate indexes measuring medium-level skills, lower-level skills, low skills with poor communication and high skills and computing competence. In the bar charts below, the mean of each index was plotted against the population grouping variable.

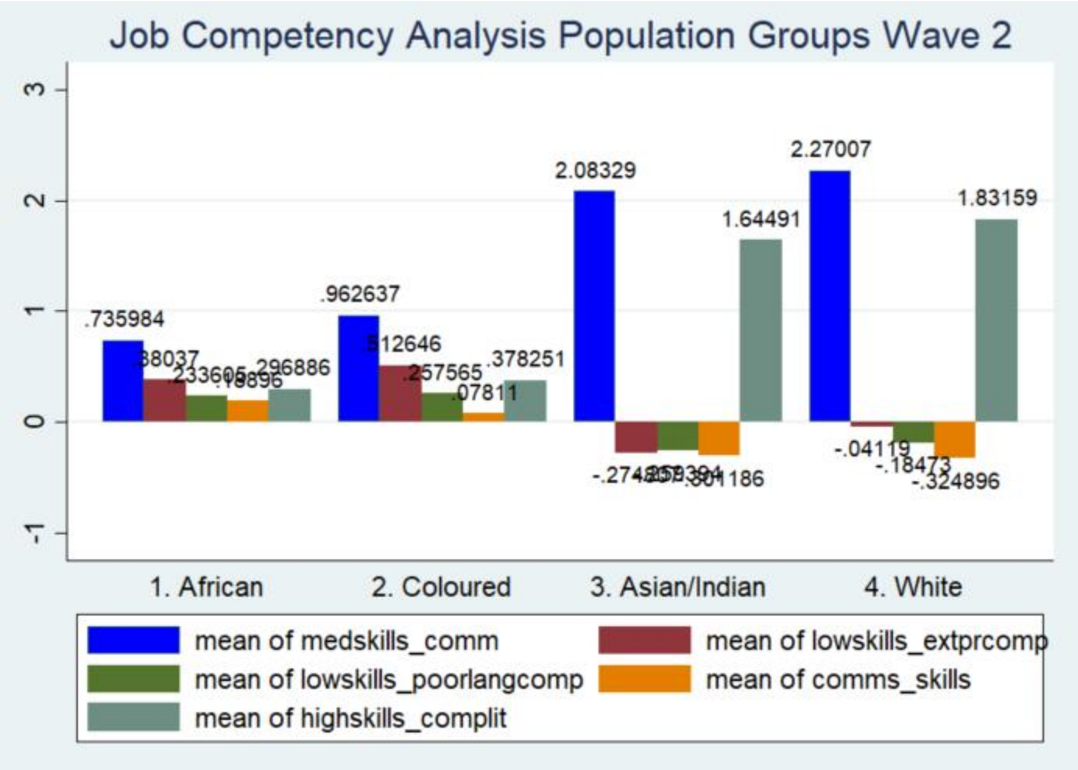
Figure 32: Job Competency assessment across population groupings Wave 1



Source: Own calculations using NIDS data.

In figure 32, which is a presentation of the analysis of the job competency index using wave 1 of the data, the mean index for medium skills across population groups, shows Africans (1.266), Coloureds (1.786), Asians/Indians (3.029) and Whites (3.454). This index is significant in this study, as is shown in chapter 6, medium levels skills are at the highest risk of automation and technology displacement, while at the same time, forming the springboard of skillset for the new digital economy. This mean index is composed of medium skills, basic computer literacy and proficiency in both verbal and written English, representing the bulk of employees in the labour market. Whites (2.164) and Asians/Indians (1.315) have the high mean indexes for high skills with computer literacy, which skills are at very low risk of automation at least in the early stages of DT (World Economic Forum, 2016), within this category, Africans have the lowest mean index. Africans have the highest mean index of low skills with poor computer skills, although they had a higher mean index for communication skills (verbal and written the English language). The negative index values on low skills with good communication and low skills with poor language competency among Asians/Indians (-0.34, -0.22) and Whites (-0.36, -0.17), respectively, shows the placement of these groups on the medium and high-end skills competencies categories as shown in the chart, as the negative mean index shows the opposite placement within that category. Overall, the African population group performed very poorly concerning the job competency index when assessed against other population groupings, and with serious implications for a population group that composes the highest proportion of labour market participants.

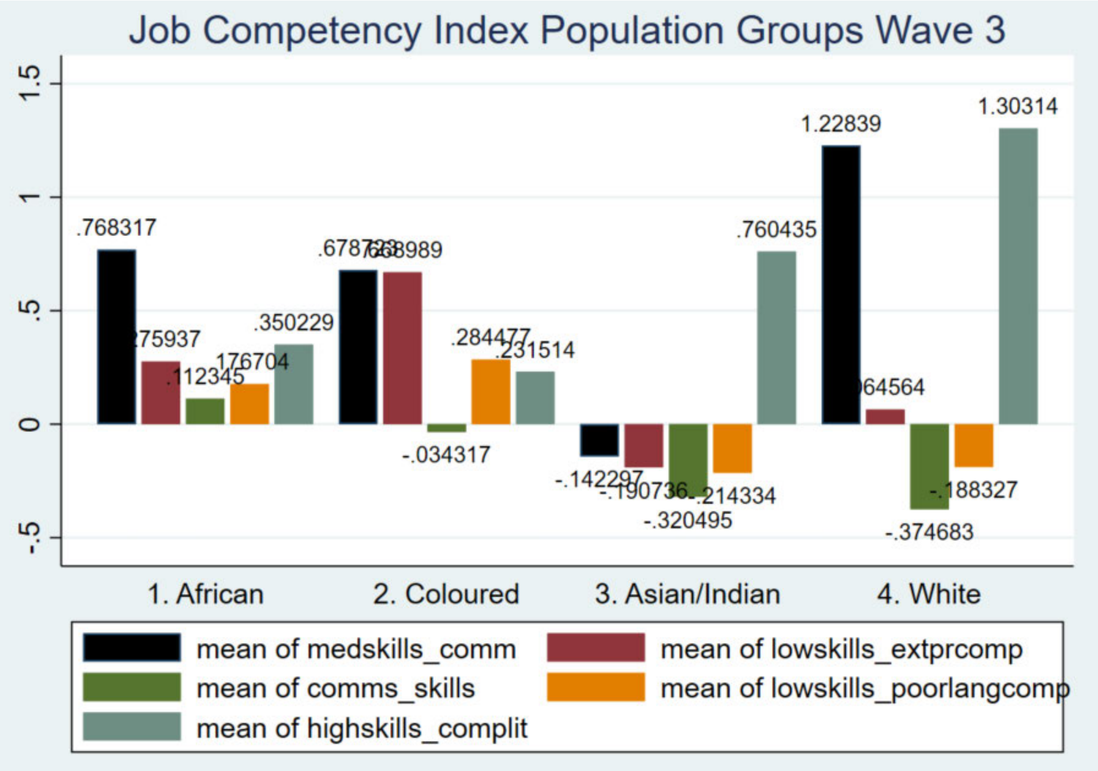
Figure 33: Job Competency across Population groupings Wave 2



Source: Own calculations using NIDS dataset.

In the analysis of wave 2 data presented in figure 33, the White and Asian/Indian population groups showed high marginal mean indexes in medium and high skilled categories, significantly large showing increased gains in these skills categories in these population subgroups at the time of wave 2. The mean index for medium and high skills for the African population group continued to show gains although the marginal index was smaller than its previous level, even though the gain is positive yet the comparable rate is smaller. The Asians/Indians and Whites continued to show negative mean indexes for low skills categories both with good and poor English competency and communication skills while showing higher representation in medium and higher-end skills. The larger labour reserve, the African population group, does not feature predominantly in the medium and high-end skills categories, which creates skewed skills divide and income distribution since medium and high-end skills have higher compensation than low-end skills. The size of the African population subgroup and its prevalence with the low skilled labour, low levels of communication skills and poor language competency may be indicative of the magnitude of skilling needs and the size of interventions that might be needed to equip vast numbers of people at high risk of job displacement due to digital transformation.

Figure 34: Job Competency Index across Population Groups, Wave 3

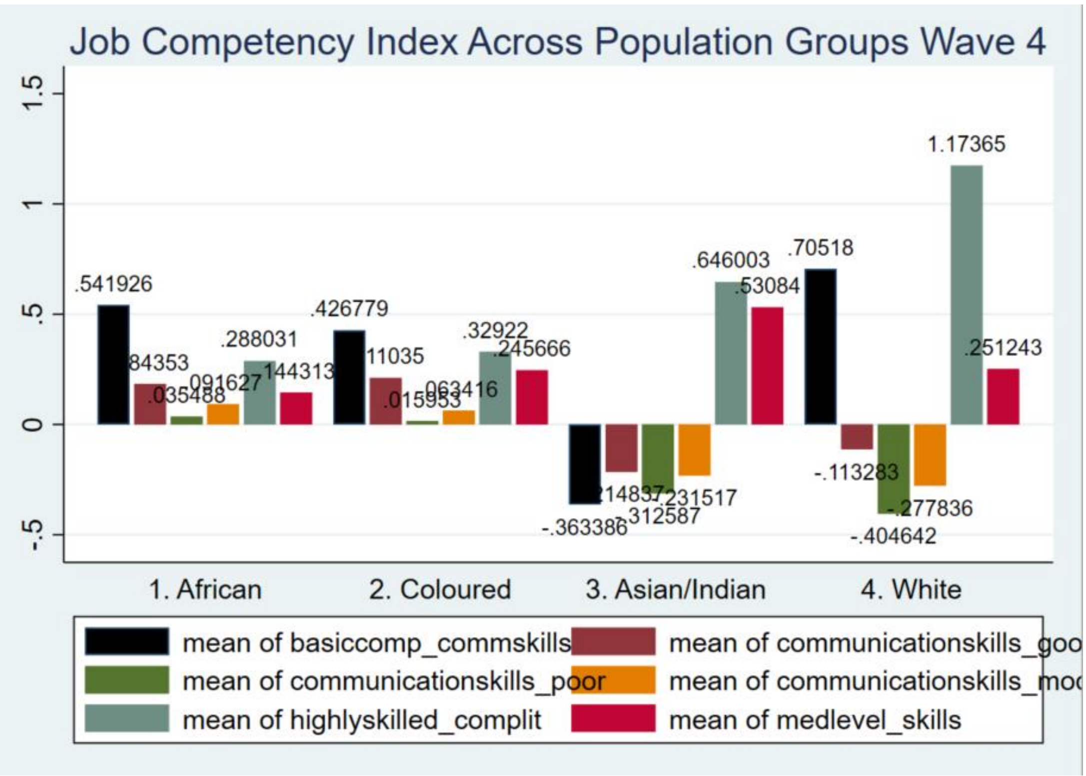


Source: Own calculations using NIDS data.

The analysis of wave 3 of the data presented in figure 34 above showed a transition in the mean index for middle job skills, such that while the mean index has remained high for the White population group (1.23), the African population group has shown some significant gains in the medium skills sector as shown by a comparably higher positive marginal index, while the Asian/Indian population group showed a marginal decline in the mean index across all skills categories except for high-end skills, which have remained comparatively higher. This shift showed a transition in skills among population groups, with increased competition in the medium to low skills sectors forcing the other groups to move towards high-end competencies with less competition. This is quite significant given the structural unemployment challenge in South Africa, based on skills that have since persisted (Banda, Ngirande and Hogwe, 2016). The Asian/Indian population seemed to have shifted towards gaining high-end skills, given the high marginal index on high-end competencies with negative indices for all other skills categories, showing a marginal decline in the prevalence of these groups in low to middle-skilled labour during this period.

In the analysis of wave 4 of the data presented in figure 35, the index values showed further decomposition for basic computer and communication skills, good communication skills, moderate communication skills, poor communication skills, medium level skills and high skills with computer proficiency. Whites (0.71) and Africans (0.54) had high indexes for basic computer and communication skills. Whites (1.17) and Asians/Indians (0.64) continued to dominate the high-end skills sector and somewhat of the medium skills sector with mean indexes 0.25 and 0.53 respectively, and in terms of the marginal increase in the prevalence of these skillsets amongst these groups. Thus, the divide in skills according to population grouping remained with its implications in terms of socioeconomic outcomes, particularly income distribution.

Figure 35: Job Competency Index Across Population Groups, Wave 4

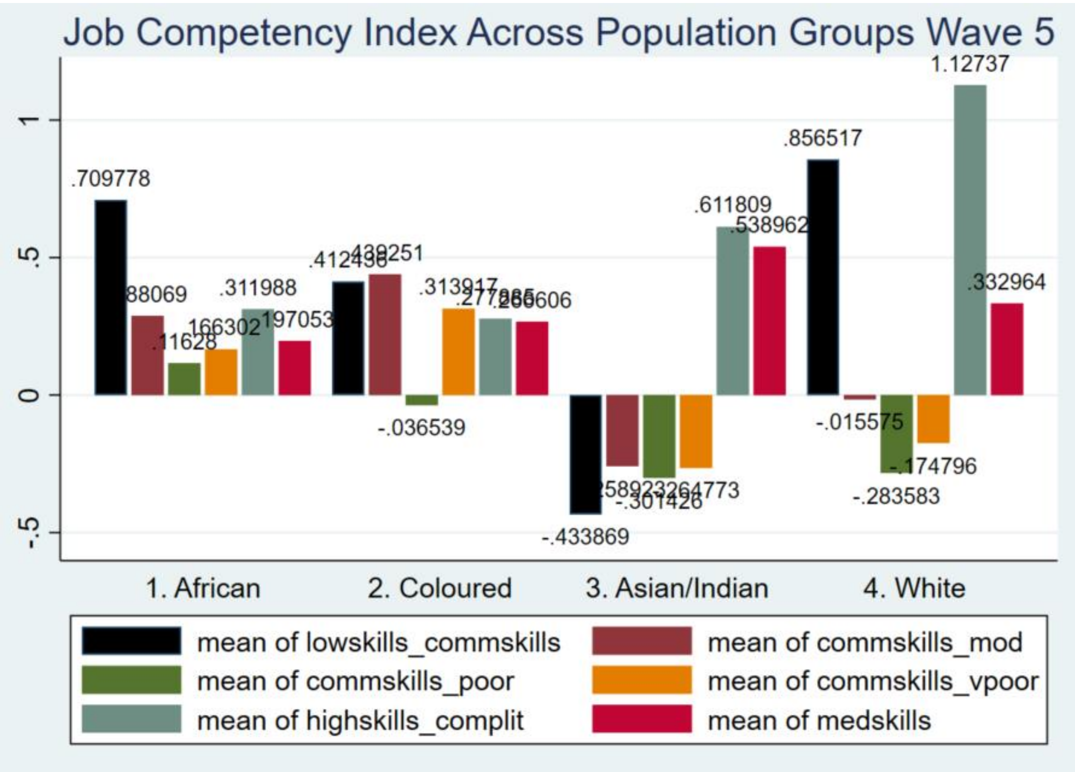


Source Own calculations using NIDS data.

In the analysis of wave 5 of the data presented in figure 36 below, Whites and Asians/Indians continued to dominate the high-end skills sector, and have relatively high marginal mean indexes for medium skills. There is some improvement in the African and Coloured population groups along all metrics given previous performance in waves 1 through 4, while Asian/Indians have negative marginal mean indexes in all metrics except for medium and high-end skills. The marginal mean index of low skilled labour showed a significant gain for the African population group (0.71) and Whites (0.86), while for medium skills the marginal gain for the African population group has remained very small.

The analysis from waves 1 through 5, shows that there is a significant divide in sectoral participation across population groups, with the largest labour reserve performing poorly in the medium and high-end skills categories, with socioeconomic implications, particularly the structure of income distribution. This also shows that the largest share of the labour reserve is not fully equipped and employed in highly productive engagement in the economy, or inversely there is a dependence on high-end skills from an increasingly smaller segment of the population resulting in skewed socioeconomic outcomes, particularly income redistribution.

Figure 36: Job Competency Index Across Population Groups Wave 5



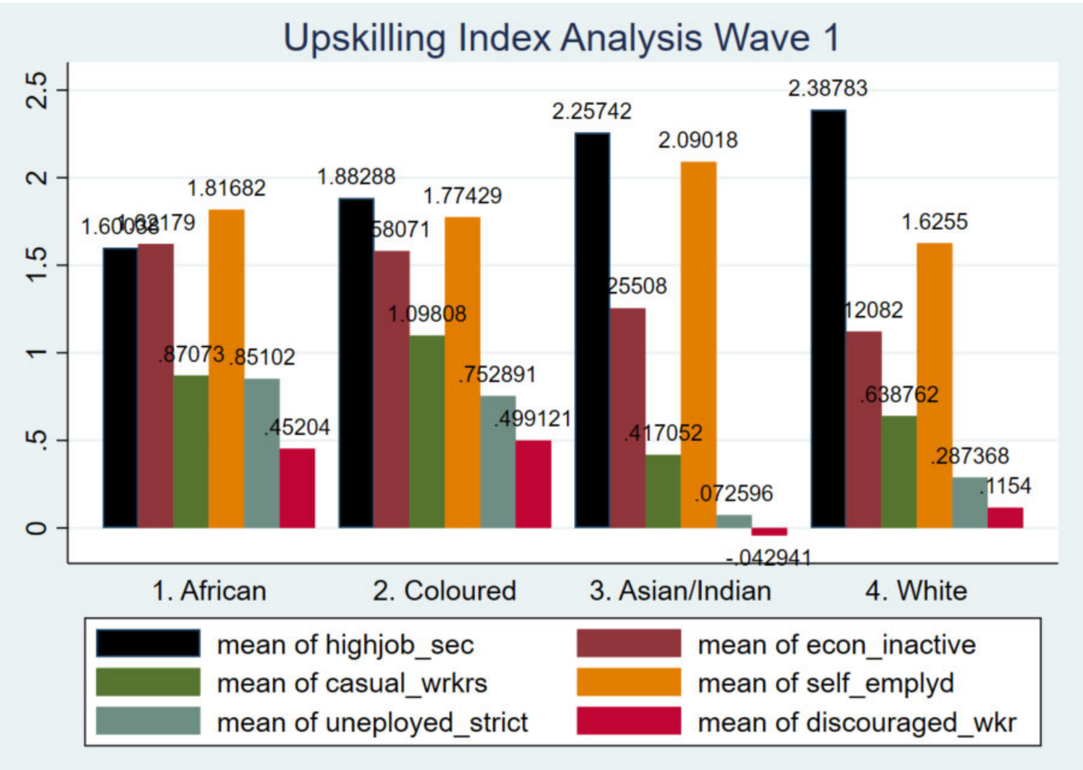
Source: Own calculations using NIDS dataset

5.9.2. The Upskilling Index

Among the most ambitious indexes presented in this research study given the nature of the quantitative dataset is the upskilling index. It attempted to measure those who were likely to receive in-house training and upskilling opportunities in the labour force. The analysis was conducted across the years to assess changes over every 2 years from 2008 when the first survey of the national incomes' dynamics study was published (Brophy *et al.*, 2018). Individuals were assessed whether they were employed in the private sector, the public sector, self-employed or other forms of employment.

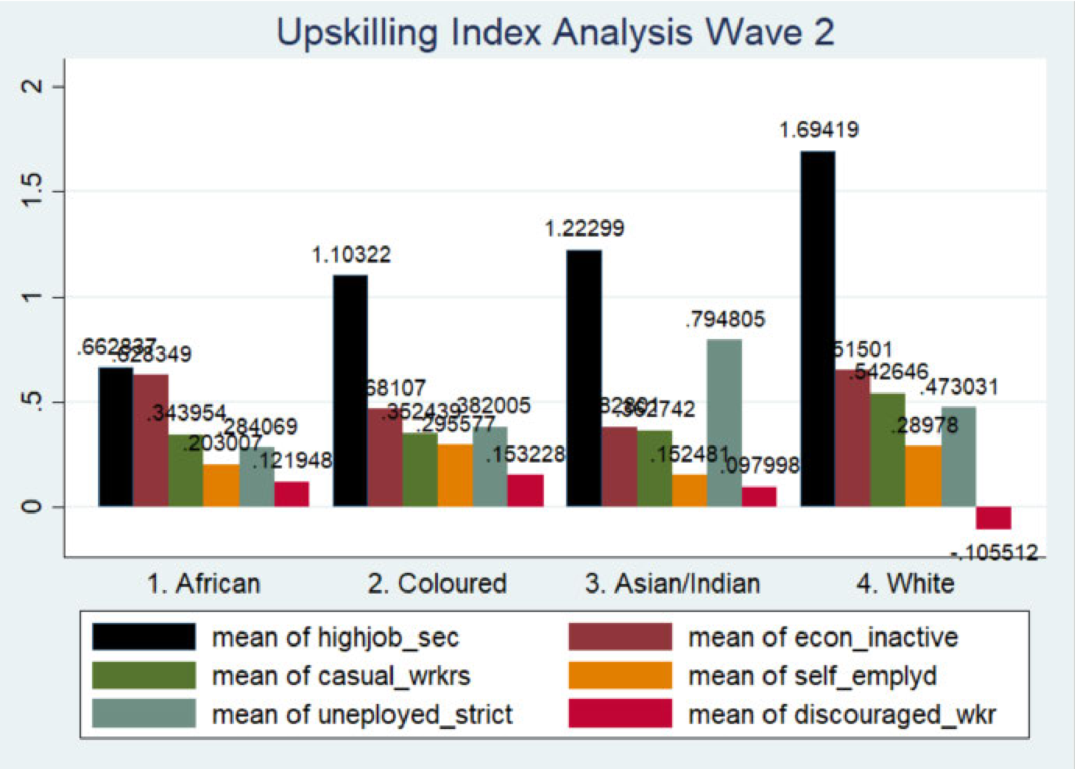
The results of the analysis of the upskilling index in wave 1 of the dataset, presented in figure 37 shows plots of 6 mean indexes measuring highly secure employment, casual work, unemployed people according to the strict definition of unemployment, the economically inactive, the self-employed and discouraged individuals (low skilled and economically marginalised), charted across population groupings. The chart shows high values of the mean index for highly secure employment for Whites (2.39), Asians/Indians (2.26), Coloureds (1.88) and Africans (1.60). Africans had the highest mean index of economic inactivity with a mean index just marginally above that of Coloureds. The mean index of self-employment has Asians/Indians (2.09), Africans (1.82), Coloureds (1.77) and Whites (1.63). The largest share of discouraged workers by mean values is for Coloureds (0.50) and Africans (0.45), while the Whites had the smallest share (0.12) and no discouraged workers among Asians/Indians (-0.04). Employers of those with high employment security may make in-house skills upgrading, retraining and reskilling available, while all other categories of work, place the upskilling burden on the individuals and households.

Figure 37: Upskilling index Analysis Wave 1



Source: Own calculations using NIDS data.

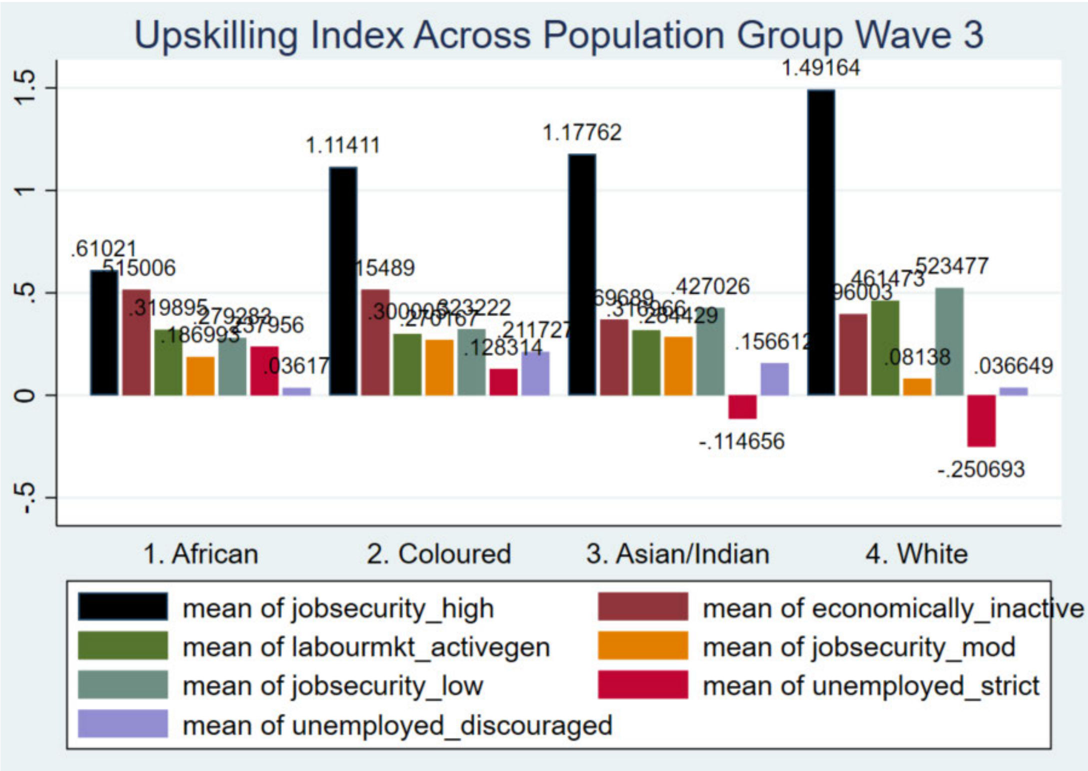
Figure 38: Upskilling Index Analysis Wave 2



Source: Own calculations using NIDS dataset.

In the analysis of wave 2 of the dataset presented in figure 38, Whites continued to have the highest mean index for secure employment (1.69), followed by Asians/Indians (1.22), Coloureds (1.10) and finally Africans (0.66). The share of the economically inactive population is highest among the African population group and followed by the White population group with mean index values 0.63 and 0.52 respectively. The analysis also shows that there is a high mean index of self-employment among Coloureds and Whites, although the mean indexes are not significantly different given the values of the mean indexes among the two groups, such population share represented might be of usefulness in estimating the real impact of the differences. These indexes convey information on the divide in employment inequalities, however, the deeper mechanics is job competencies, assessed and presented in 5.8, where the dominance of the White and Asian/Indian population in high-end skills and middle-income jobs was shown. High-end skills are scarce skills and associated with secure employment due to the challenges of talent recruitment in high-end skill-intensive jobs.

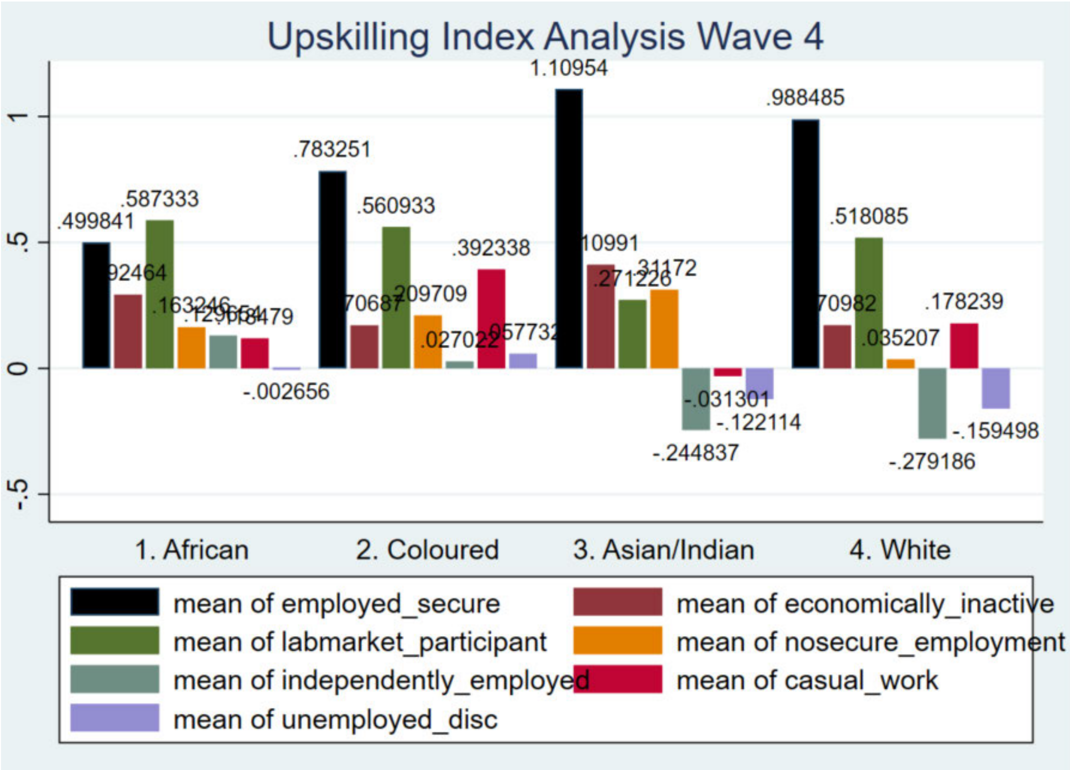
Figure 39: Upskilling Index Analysis, Wave 3



Source: Own calculations using NIDS dataset.

The analysis of wave 3 of the data presented in figure 39, continued to show more or less the same employment divide, among population groups. The mean index of highly secure employment continued to be concentrated among Whites (1.49), Asians/Indians (1.18) and Coloureds (1.11). Among Africans, the marginal mean index was below 1, meaning change is evident but at a very low level given the size of the population subgroup. If the mean is understood as showing change, what is observed from wave 1 through to wave 3 is continued dominance of the White population subgroup in secure employment, although the rate of change in the dominance is marginally declining from 2.39 to 1.68 and 1.49 in waves 1, 2 and 3 respectively. This change is not limited only to the White population group, but is observable among all population groups, meaning that over time, the share of secure employment across population groups is showing a marginal decline. This could be attributable to a lower rate of growth of secure forms of employment around this time, and the increasing size of the contribution of the service sector to the national product (Zaakhir, Bhorat and Page, 2020).

Figure 40: Upskilling Index Analysis Across Population Groups, Wave 4



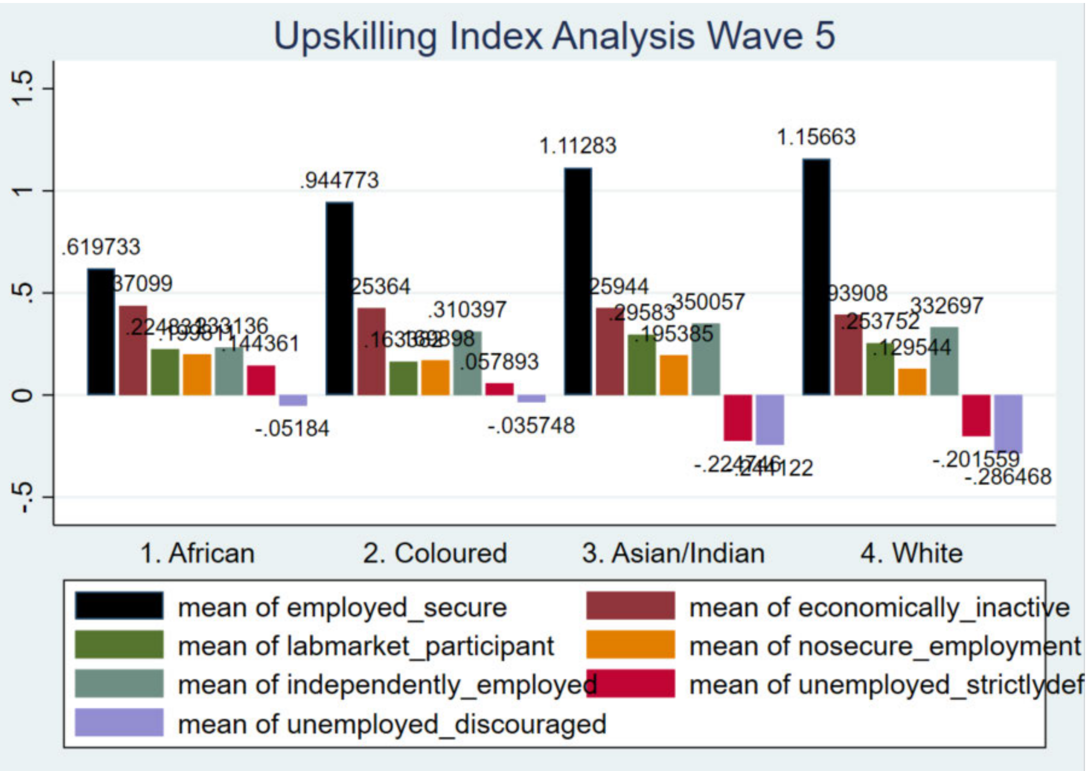
Source: Own calculation using NIDS data.

The analysis of wave 4 of the data presented in figure 40, continued to show only marginal change, particularly in the mean index for secure employment opportunities. From wave 3 the mean index for Whites fell 33.7 per cent to its value in wave 4, where the mean index is less than 1. There was a small marginal decline in the mean index for Africans in secure employment although positive, while Indians continued to show a higher marginal gain in prevalence of secure employment. There are changes across all indices measuring different aspects of work from secure employment, labour market participation, economically inactive workers, insecure employment, casual work, self-employment and discouraged workers. In wave 4 the marginal rise in labour market participation among Africans is significant and higher than for all other population groups. However, the employment divide remains particularly concerning access to secure employment since this is determined by the competencies or skills divide, which is skewed across population groups because of access to opportunities for personal development.

The analysis for wave 5 of the data presented in figure 41, showed the same employment divide among population groups, with Whites having a higher mean index than other population groups. The negative mean index on discouraged workers shows marginal decline across all population groups, although the marginal declines are different for all groups. It can also be observed that the negative mean index for unemployed and discouraged workers is larger for Whites and Asians/Indians than for other population groups. Unemployment according to the strict definition showed a negative mean index for Whites and Asians/Indians, while it remained positive for Africans and Coloureds.

The longitudinal analysis thus showed an employment divide. The change in the share of secure employment has been marginal across the waves remaining largely the same throughout, as Whites continued to show larger marginal mean indexes, showing quite robust positive change in access to secure employment, while the change for Africans has remained marginally constant. What this shows is if training opportunities are going to be provided through businesses, government and other employment institutions, which offer secure employment, then upskilling will be available to a fraction of the population. This analysis also shows individuals in other forms of employment which are not secure will be the least likely to access upskilling, and given the picture of skills and employment observed, might mean long-run inequalities since the ability to skill and upskill oneself across the waves is explained by the picture of the employment divide that has been presented thus far.

Figure 41: Upskilling Index Assessment Across Population Groups Wave 5



Source: Own calculations using NIDS dataset.

5.9.1. Concluding thoughts on descriptive analysis

The descriptive analysis of the national income dynamics study data on various measures of socioeconomic welfare such as human capital, socioeconomic status, social inclusion, access to digital technologies and labour market participation (the key institution of income distribution in South Africa) has shown a consistent portrayal of a resilient divide with group underpinnings. As also outlined in the presentation of the results, the effect of DT will largely depend on the status of this divide along multiple lines in terms of household opportunities, individual opportunities, institutional participation and developmental opportunities. Resolving this divide will be among the key policies and interventions requiring implementation to advance broad socio-economic welfare.

5.10. Regression Analysis: DT and the socioeconomic divide

In Chapter 2 the discussion of the theoretical model of endogenous growth which purports to explain digital technology index as a function of various socioeconomic variables among them, access to clean energy, social exclusion, human capital and other functionalities that enable individual access to and participation in the labour market. In assessing this as an overall objective of the study, a multiple linear regression model was modelled on the NIDS data, to assess the effect of socio-economic, exclusion, skills, job competency and upskilling prospects on the decomposed measures of the digital index. The analysis was run for each of the four sub-indexes of the digital technology index. The results are presented in tables, with exponentiation being implemented on the final model, such that the results presented show the effect of a one-unit change in the feature variables on the digital index sub-indexes, the response variables, enabling the model to be used for forecasting. For each regression coefficient, the associated p-value is presented in parenthesis under each coefficient to show that only coefficient significant at 5% level were included in the final model.

5.10.1 Regression Analysis for NIDS Wave 1 Data.

Table 12: Modelling the Comprehensive Digital Index

Survey: Linear regression

Number of strata = 53	Number of obs = 7,296
Number of PSUs = 401	Population size = 13,972,673
	Design df = 348
	F(14, 335) = 39.80
	Prob > F = 0.0000
	R-squared = 0.1978

comp_dig_index	exp(coef.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
population_grp						
2	.5030085	.0638572	-5.41	0.000	.3918661	.6456734
3	.3516884	.0863714	-4.26	0.000	.2169607	.5700787
4	.5398434	.0687272	-4.84	0.000	.4202653	.693445
highlyq_proff	.9222737	.0235859	-3.16	0.002	.8770321	.9698491
technical_skills	.8981165	.0363116	-2.66	0.008	.8294644	.9724506
matric_unskilled	.9653131	.0153311	-2.22	0.027	.9356259	.9959422
serv_access	.9344001	.0085658	-7.40	0.000	.9177039	.9514001
labmkt_act	1.050087	.0070963	7.23	0.000	1.036222	1.064137
mod_prefleave	1.02316	.0095628	2.45	0.015	1.004523	1.042142
commercial_inf	.9499137	.0192682	-2.53	0.012	.912763	.9885765
noinf_access	.9233496	.0202938	-3.63	0.000	.884286	.9641389
poor_infserv	.9338938	.0157538	-4.05	0.000	.9034176	.9653981
lowskills_extprcomp	.9471671	.0098646	-5.21	0.000	.9279628	.9667688
lowskills_poorlangcomp	.9698885	.0086287	-3.44	0.001	.9530652	.9870088
_cons	30.36802	1.027344	100.90	0.000	28.41319	32.45734

Source: Own calculations using NIDS dataset.

In modelling the comprehensive digital index, variables measuring socioeconomic characteristics, social exclusion, job competency and skills were used as features variables in a multiple linear regression model. The overall regression model was statistically significant with an F Statistic [14, 335] of 39.80 and a p-value of 0.0000. The model containing statistically significant feature variables (Wald Statistic Prob > |t| < 0.05) explained 19.78 % of the variation in the response variable as shown by the R-squared statistics in Table 12. The model as presented in the table shows the influence of a unitary change in each feature variable on the dependent variable. Access to digital smartphones exhibited the highest loading on the comprehensive digital index. Most of the coefficients in the model are less than one ($\beta < 1$) except for labour market participation and individuals exhibiting moderate preference towards relocation with 1.05 and 1.02 respectively. Access to digital smartphones according to the model does not seem to be influenced by skills profile (highlyq_proff, technical skills, matric_unskilled), social exclusion (serv_access, labmkt_act, mod_preleave, productive infrastructure access, general infrastructure services) or skills.

Table 13: Modelling the Communication Asset Index.

Survey: Linear regression

Number of strata = 53		Number of obs	= 7,296
Number of PSUs = 401		Population size	= 13,972,673
		Design df	= 348
		F(19, 330)	= 50.23
		Prob > F	= 0.0000
		R-squared	= 0.5360

comms_asset_index	exp(coef.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	.6107526	.0855306	-3.52	0.000	.4637095	.8044233
population_grp						
2	2.20494	.604357	2.88	0.004	1.2861	3.780235
3	3.84793	2.520171	2.06	0.040	1.061192	13.95277
4	7.253902	2.325826	6.18	0.000	3.860981	13.62843
highlyq_proff	1.417882	.1378247	3.59	0.000	1.171145	1.716602
sedentary	.8761952	.0399149	-2.90	0.004	.8011045	.9583243
serv_access	1.133903	.0295284	4.83	0.000	1.077288	1.193492
labmkt_act	.8387948	.0323847	-4.55	0.000	.7774587	.9049698
access_devopp	1.140092	.0378098	3.95	0.000	1.0681	1.216935
mod_prefleave	.8620705	.0271376	-4.71	0.000	.8103149	.9171319
commercial_inf	1.909824	.1045504	11.82	0.000	1.714877	2.126933
stable_hsehld	1.297757	.0941247	3.59	0.000	1.12523	1.496737
poor_infserv	.9160988	.0439413	-1.83	0.069	.8336262	1.006731
urban_res	1.099205	.0427063	2.43	0.015	1.018339	1.186492
medskills_comm	1.206932	.0728689	3.12	0.002	1.071796	1.359108
lowskills_extprcomp	1.222358	.061149	4.01	0.000	1.107817	1.348741
lowskills_poorlangcomp	1.166126	.0515675	3.48	0.001	1.068988	1.272091
comms_skills	1.20693	.056889	3.99	0.000	1.10007	1.32417
highskills_complit	1.200203	.0507913	4.31	0.000	1.104351	1.304375
_cons	1.82575	.3572738	3.08	0.002	1.242486	2.682816

Source: Own calculation using NIDS dataset.

In modelling the communication asset index which measured access to more advanced digital assets or devices and facilities, the multiple linear regression model with F (19, 330) of 50.23, and a model p-value of 0.0000, explained 53.60 % of the variation in the response variable based on the contribution of the feature variables. For a one-unit change in each feature variable, holding other features constant, Whites had more access to advanced technologies than Africans in the sample by a factor of 7.25, Indians by a factor of 3.85 and Coloureds by a factor of 2.21. The coefficients on population grouping have a large influence on the response variable. The influence of spatial location is significant but small (0.61) for each unitary change, that is changing location from rural to urban improves communication asset index by 0.61. Professional status (1.42), access to services (1.13), access to developmental opportunities (1.14) access to productive capital (1.91), household stability (1.29), medium-skilled individuals (1.21), low computer skills (1.22), communication skills (1.21) and high skills (1.20) influence the response variable by at least 1 point. As individuals are more likely to advance in the direction of these indexes, the more likely they are to have access to advanced digital technologies, although the influence of population grouping is high. Other studies have also identified economic, political and social factors contributing to inequities observed in access to digital technologies and affect large scale digital adoption (Joseph and Andrew, 2007; Smidt, 2021). An earlier study confirmed challenges in mobility and less hands-on computer experience as hindering women's socioeconomic welfare and empowerment (Joseph and Andrew, 2007).

Table 14: Modelling the Index of Computer Skills.

Survey: Linear regression

Number of strata = 53		Number of obs	= 7,296
Number of PSUs = 401		Population size	= 13,972,673
		Design df	= 348
		F(16, 333)	= 122.59
		Prob > F	= 0.0000
		R-squared	= 0.6636

comp_lit_index	exp(coef.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
4.population_grp	1.878391	.3785124	3.13	0.002	1.263754	2.79196
cert_financialserv	.9166874	.0223133	-3.57	0.000	.8738354	.9616408
highlyq_proff	1.192698	.0539918	3.89	0.000	1.091097	1.30376
exp_construction	1.108846	.0241581	4.74	0.000	1.062336	1.157393
exp_translog	.9029023	.0187578	-4.92	0.000	.866753	.9405592
sedentary	.7987538	.0175633	-10.22	0.000	.7649465	.8340553
labmkt_act	.7994963	.0191455	-9.34	0.000	.7627138	.8380527
mod_prefleave	.9276552	.0157806	-4.41	0.000	.8971314	.9592176
commercial_inf	1.232698	.0465764	5.54	0.000	1.144413	1.327795
stable_hsehld	1.116875	.0331225	3.73	0.000	1.053593	1.183957
poor_infserv	.9229401	.0230608	-3.21	0.001	.8786804	.9694292
medskills_comm	1.618612	.0611497	12.75	0.000	1.502702	1.743462
lowskills_extprcomp	1.507062	.0441255	14.01	0.000	1.422727	1.596395
lowskills_poorlangcomp	1.402513	.0328278	14.45	0.000	1.339411	1.468589
comms_skills	1.476198	.0399766	14.38	0.000	1.399629	1.556955
highskills_complit	2.440693	.06341	34.34	0.000	2.31911	2.568649
_cons	.7385033	.0421008	-5.32	0.000	.6601728	.826128

Source: Own calculation using NIDS dataset.

In modelling the computer skills index using the multiple linear regression model, the model with F statistic [16, 333] of 122.59 and an overall p-value of 0.0000, the model explained 66.36

% of the variation in the computing skills index based on the statistically significant feature variables in the model. For each 1-unit change in the explanatory variables, the computing index increases by 1.88 units for Whites when compared with Africans holding other features constant. Professional status increases computing skills index by 1.19, experienced construction work by 1.11, access to productive capital by 1.23 and household stability by 1.11. The high coefficient on advanced computing skills (2.44) shows that the computing skills index captured the influence of computer skills and usage among competencies and socioeconomic characteristics in the data.

Table 15: Modelling the Index for Low Access to Digital Technologies.

Survey: Linear regression

Number of strata	= 53	Number of obs	= 7,296
Number of PSUs	= 401	Population size	= 13,972,673
		Design df	= 348
		F(15, 334)	= 128.29
		Prob > F	= 0.0000
		R-squared	= 0.6077

low_dig_index	exp(coef.)	Linearized std. err.	t	P>|t|	[95% conf. interval]	
cert_financialserv	1.068647	.0166633	4.26	0.000	1.036371	1.101928
highlyq_proff	.8887555	.0375255	-2.79	0.006	.8179316	.965712
exp_construction	.8711117	.0143047	-8.40	0.000	.8434266	.8997055
exp_translog	1.07146	.0171966	4.30	0.000	1.038166	1.105822
sedentary	.8287296	.0185181	-8.41	0.000	.7930969	.8659632
serv_access	1.052113	.0097909	5.46	0.000	1.033031	1.071547
labmkt_act	.8030228	.0190608	-9.24	0.000	.7663955	.8414006
access_devopp	1.048872	.0138625	3.61	0.000	1.021958	1.076494
commercial_inf	1.111453	.032683	3.59	0.000	1.048995	1.177629
urbanpoor_hsng	1.081437	.0239076	3.54	0.000	1.035424	1.129496
medskills_comm	2.483388	.0803613	28.11	0.000	2.330258	2.646581
lowskills_extprcomp	1.458031	.0373626	14.72	0.000	1.386368	1.5334
lowskills_poorlangcomp	1.37861	.0287758	15.38	0.000	1.32316	1.436385
comms_skills	1.570654	.0359076	19.75	0.000	1.501595	1.642889
highskills_complit	.8205652	.0221339	-7.33	0.000	.7781667	.8652737
_cons	.5384576	.0321119	-10.38	0.000	.4788631	.6054686

Source: Own calculation using NIDS dataset.

In modelling the index for low access to digital technologies, the multiple regression model with an F Statistic [15, 334] of 128.29 and an overall model p-value of 0.0000 explained 60.77 % of the variation in the low digital index, the response variable. Low to medium-skilled competencies contribute significantly to the low digital index. The low digital index increases by 2.48 for medium-skilled individuals, 1.45 for low skilled individuals, 1.37 for low skilled individuals with poor communication abilities, 1.57 for communication skills and 1.07 for individuals in transport and logistics careers. Low skilled occupations are thus demonstrated to be associated with the low digital index. This aligns with the argument proposed in the digital transformation literature that skills and forms of employment with low digital composition may be at risk of technology-induced displacement (Acemoglu and Restrepo, 2019; Peters and Jandrić, 2019).

5.10.2 Regression Analysis for NIDS Wave 2

In the regression analysis using wave 2 of the data, the disaggregation focused on 4 sub-indexes, the comprehensive digital asset index, the communication asset index, the advanced computing skills index, the basic computing skills index and the internet access index. The results of the multiple linear regression analysis are presented in Tables 16 to 20.

Table 16: Modelling the Comprehensive Digital Index Wave 2

```
Survey: Linear regression

Number of strata =     53                    Number of obs   =      5,385
Number of PSUs   = 5,385                     Population size = 5,593,706
                                             Design df       =      5,332
                                             F(12, 5321)     =      20.50
                                             Prob > F        =     0.0000
                                             R-squared       =     0.1500
```

comp_dig_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	.8023786	.0520738	-3.39	0.001	.7065198	.9112431
population_grp						
2	.4918021	.0597636	-5.84	0.000	.3875513	.6240961
3	.3547052	.1017181	-3.61	0.000	.2021691	.6223294
4	.3333226	.0534295	-6.85	0.000	.2434398	.4563919
sedentary	.9657069	.0108754	-3.10	0.002	.9446203	.9872642
marg_active	1.052483	.0108219	4.97	0.000	1.03148	1.073914
labmkt_act	1.037932	.0166043	2.33	0.020	1.005886	1.070999
access_devopp	1.021656	.0076502	2.86	0.004	1.006768	1.036764
midinc_univ_cc	1.020358	.0072486	2.84	0.005	1.006246	1.034668
commercial_inf	1.092663	.0211914	4.57	0.000	1.051899	1.135007
noinf_access	.9243656	.0190662	-3.81	0.000	.8877338	.9625091
poor_infserv	.949051	.021924	-2.26	0.024	.9070296	.9930191
_cons	27.91368	2.444757	38.01	0.000	23.50984	33.14245

Source: Own calculation using NIDS dataset.

The multiple linear regression with an F Statistic [12, 5321] of 20.50 and an overall p-value of 0.0000, explained 15% of the variation in the comprehensive digital asset index. The mean value of the comprehensive index with zero explanatory variables shows a highly significant coefficient on the multiple regression constant (27.91). As observed in the regression model for Wave, the poor contribution of socioeconomic characteristics, exclusion or skills in explaining variable in the response variable, shows that access to digital smartphones is explained by other motivating variables than those accounted for in the present regression model. This outcome implies that changes in access to digital smartphones are not influenced significantly by socioeconomic characteristics, social exclusion or skills and hence influences on these variables cannot shape this extent to any significant extent. This finding does not seem to align with findings in other studies that attribute a large influence of socioeconomic factors on access to digital or mobile devices for development (Conradie D.P., Morris C., and Jacobs S.J., 2003; Diga, Nwaiwu and Plantinga, 2013).

Table 17: Modelling the Communication Asset Index Wave 2

Survey: Linear regression

Number of strata	= 53	Number of obs	= 5,385
Number of PSUs	= 5,385	Population size	= 5,593,706
		Design df	= 5,332
		F(9, 5324)	= 97.03
		Prob > F	= 0.0000
		R-squared	= 0.4462

comms_asset_in~x	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	1.380842	.1765433	2.52	0.012	1.074711	1.774175
4.population_grp	5.76088	2.115292	4.77	0.000	2.804606	11.8333
serv_access	1.104409	.0307536	3.57	0.000	1.045736	1.166375
access_devopp	.9490126	.0182119	-2.73	0.006	.9139731	.9853955
midinc_univ_cc	.9386089	.0182155	-3.26	0.001	.9035699	.9750066
commercial_inf	1.224058	.0556812	4.44	0.000	1.119626	1.338231
noinf_access	1.3207	.0553022	6.64	0.000	1.216616	1.433689
stable_hsehld	1.80254	.1261141	8.42	0.000	1.571511	2.067533
poor_infserv	1.313654	.0575991	6.22	0.000	1.205454	1.431567
_cons	1.77567	.1242847	8.20	0.000	1.547999	2.036827

Source: Own calculation using NIDS dataset.

In modelling the communication asset index in wave 2 as shown in table 17, the multiple regression model with an F Statistic [9, 5324] of 97.03 and a model p-value of 0.0000 showing the model was statistically significant, explained 44.62 % of the variation in the response variable based on the feature variables. The significant influence of population grouping remains as being in the White population group raises the communication asset index by 5.76 points (4. population_grp) as compared to being in the African population group. The importance of population grouping seems to be declining when the influence of this factor is compared for wave 1 and wave 2. Thus, the racial dynamics continued to influence access to more advanced digital technologies. Being located in urban areas (2. spatial) raises the communication asset by 1.38 points for every 1unit increase in spatial geography towards urban areas. Household stability (stable_hsehld) raises the communication asset index by 1.80 points for every 1 unit increase in the index of household stability. Thus, the model shows that access to advanced digital technology is positively associated with population grouping, spatial location, access to services, productive capital assets, infrastructure services, and household stability. Taking into consideration that the survey for NIDS wave 2 was conducted in the 2 years leading to 2010, the findings of this model regarding access to digital technologies are confirmed by an empirical study that showed that access and opportunity were key determinants of digital access. The study also argued that the observed tendency towards digital democracy existed in the form of a mobile society that is not age-specific and ubiquitous (Brown and Czerniewicz, 2010). Another study observed social and economic exclusion as challenges towards advanced digital technology access among South African students (Oyedemi, 2012). These studies confirm the findings from the empirical model being used in this study.

Table 18: Modelling the Computer Skills Index Wave 2

Survey: Linear regression

Number of strata = 53	Number of obs = 5,445
Number of PSUs = 5,445	Population size = 5,675,688
	Design df = 5,392
	F(10, 5383) = 85.29
	Prob > F = 0.0000
	R-squared = 0.6009

comp_lit_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
4.population_grp	2.286206	.5735978	3.30	0.001	1.397994	3.738743
exp_construction	1.102283	.030273	3.55	0.000	1.044506	1.163257
access_devopp	1.018314	.008005	2.31	0.021	1.002741	1.034129
midinc_univ_cc	1.023103	.0079861	2.93	0.003	1.007566	1.038879
stable_hsehld	1.229966	.0577261	4.41	0.000	1.12185	1.348502
urbanpoor_hsng	1.166721	.0511337	3.52	0.000	1.070663	1.271396
medskills_comm	1.122888	.0239691	5.43	0.000	1.076868	1.170874
comms_skills	1.040266	.0110203	3.73	0.000	1.018884	1.062096
highskills_complit	2.149582	.0684722	24.02	0.000	2.019455	2.288096
uneployed_strict	1.057313	.0275652	2.14	0.033	1.004632	1.112757
_cons	.8530732	.026988	-5.02	0.000	.8017732	.9076556

Source: Own calculations using NIDS data.

In modelling the computer skills index, the multiple regression model with an F Statistic [10, 5383] of 85.29 and a model p-value of 0.0000 demonstrating the overall statistical significance of the MLR model, explained 60.09 % of the variance in the response variable based on the feature variables. The model shows that the computing skills index is positively associated with population grouping increasing by 2.28 points for every individual in the White population grouping compared with each individual in the African population grouping, skilled construction work (1.10), access to developmental opportunities (1.01), middle-income family background (1.02), household stability (1.23), urban location (1.16), communication skills (1.04), frictional unemployment (1.05) and advanced computing skills (2.15). These explanatory variables are subgroups of socioeconomic characteristics (population grouping, occupational categories and household characteristics) and social exclusion/inclusion (labour market access and access to developmental opportunities. In a study on digital inequalities among university students, socioeconomic background of students and social exclusion were found to influence digital inequities and exacerbate the social inequalities among students (Oyedemi, 2012).

Table 19: Modelling the index for low access to digital technologies Wave 2.

Survey: Linear regression

Number of strata =	53	Number of obs =	5,445
Number of PSUs =	5,445	Population size =	5,675,688
		Design df =	5,392
		F(14, 5379) =	115.12
		Prob > F =	0.0000
		R-squared =	0.5505

low_dig_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
cert_financialserv	.9448634	.0189577	-2.83	0.005	.90842	.9827687
exp_construction	.923542	.0154035	-4.77	0.000	.8938334	.9542381
highlyq_proff	1.074486	.027426	2.81	0.005	1.022043	1.12962
exp_translog	1.081776	.012866	6.61	0.000	1.056845	1.107295
sedentary	.890858	.0120421	-8.55	0.000	.8675607	.9147809
access_devopp	.9499034	.0229104	-2.13	0.033	.906035	.9958958
midinc_univ_cc	.929569	.0213721	-3.18	0.001	.8886012	.9724256
stable_hsehld	1.079676	.0220989	3.75	0.000	1.037211	1.12388
urbanpoor_hsng	.7102478	.0287556	-8.45	0.000	.6560542	.768918
medskills_comm	1.887599	.0407031	29.46	0.000	1.809467	1.969104
comms_skills	1.112244	.0143413	8.25	0.000	1.084482	1.140717
lowskills_extprcomp	1.282393	.0236017	13.51	0.000	1.236949	1.329506
highskills_complit	.7456789	.0111082	-19.70	0.000	.7242172	.7677766
uneployed_strict	1.032789	.0126403	2.64	0.008	1.008304	1.057869
_cons	1.062642	.0219195	2.95	0.003	1.020528	1.106494

Source: Own calculation using NIDS dataset.

The MLR model with an F Statistic [15, 5379] of 115.12 and an overall model statistical significance given by the p-value of 0.0000, explained 55.05 of the variation in the low access to digital technology index based on feature variables (Table 19). The model shows that professional status (1.07), logistics occupation (1.08), household stability (1.07), medium job skills (1.89), communication skills (1.11), low skills (1.28) and unemployment (1.03) increases the low access to digital technology index by at least one point for every 1 unit increase in these feature variables. Thus, the model shows that low levels of digital technologies access measured by access to landline phones and other low-level digital technologies are still influenced by socioeconomic characteristics, and skills, reflecting a functional influence on digital technology consumption.

Table 20: Modelling the Access to Internet Index Wave 2

Survey: Linear regression

Number of strata	= 53	Number of obs	= 5,445
Number of PSUs	= 5,445	Population size	= 5,675,688
		Design df	= 5,392
		F(4, 5389)	= 16.54
		Prob > F	= 0.0000
		R-squared	= 0.1477

internet_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
access_devopp	1.214812	.1139628	2.07	0.038	1.010739	1.460089
midinc_univ_cc	1.250801	.107245	2.61	0.009	1.057277	1.479747
commercial_inf	1.193286	.0415244	5.08	0.000	1.114596	1.277532
stable_hsehld	1.094279	.0416159	2.37	0.018	1.015662	1.178981
_cons	1.374568	.06332	6.91	0.000	1.255876	1.504479

Source: Own calculation using NIDS dataset.

In the modelling of the internet access index, the MLR model with an F Statistic [4, 5389] of 16.54 and an overall model p-value of 0.0000 explained 14.77 % of the model variation in the internet access index. The MLR model shows that the internet access index is positively associated with access to developmental opportunities (1.21), middle-income status (1.25), access to productive capital (1.19) and household stability (1.09). In a study, the implicit cost of internet access, support systems and services influence consumption of internet services, with access to finance being the implicit cost of internet access (Brown, Letsididi and Nazeer, 2009). Socioeconomic factors such as income, education and gender have been proposed as factors influencing internet access in South Africa (Bornman, 2016). These findings converge with these earlier studies while this study focuses on various aspects of the digital index in South Africa and compares with socioeconomic factors over a longer period than covered in these earlier studies.

5.10.3. Regression modelling for Wave 3 of NIDS data

In the regression modelling of the results for Wave 3 of the NIDS data, attention is paid to contrasts with earlier findings to trace the pattern of change in the influence of feature variables on the response variables measuring different facts of the digital index. The results of the MLR models are presented in Tables 21 through Table 25.

Table 21: Modelling the Comprehensive Digital Index Wave 3

```
Survey: Linear regression

Number of strata =     53                   Number of obs    =      5,894
Number of PSUs   =  5,894                   Population size = 15,481,030
                                            Design df        =      5,841
                                            F(27, 5815)      =      19.53
                                            Prob > F         =     0.0000
                                            R-squared        =     0.2181
```

comp_dig_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.population_grp	.678876	.060492	-4.35	0.000	.5700692	.8084504
medskills_comm	1.084801	.0142139	6.21	0.000	1.057291	1.113027
lowskills_extprcomp	1.062901	.0129381	5.01	0.000	1.037838	1.08857
lowskills_poorlangcomp	1.030284	.0115053	2.67	0.008	1.007974	1.053087
highskills_complit	1.077496	.0131913	6.10	0.000	1.051943	1.103668
income_positive	1.062131	.0194745	3.29	0.001	1.024632	1.101003
hsehold_asset_index	1.088258	.0150715	6.11	0.000	1.05911	1.118209
publicwat_spring	1.043936	.0147121	3.05	0.002	1.01549	1.073179
publicwat_distantwat	1.054145	.0172645	3.22	0.001	1.020838	1.088539
lowcosthousing_mud	.9504251	.0182329	-2.65	0.008	.9153455	.986849
hsehld_employed	.9558038	.0174601	-2.47	0.013	.9221811	.9906523
modernhousing_brick	.9376979	.0223321	-2.70	0.007	.8949249	.9825151
notpvthsehld_work	1.042261	.0198398	2.17	0.030	1.004085	1.08189
socialsupport	1.055583	.0106561	5.36	0.000	1.034898	1.076681
sedentary	.9197178	.0155138	-4.96	0.000	.8898023	.950639
middle_income	.8900363	.0073022	-14.20	0.000	.8758358	.9044671
service_access	1.037401	.008441	4.51	0.000	1.020985	1.054082
well_to_do2	.9723194	.0125887	-2.17	0.030	.9479514	.9973138
preftostay_mod	.9715906	.0142846	-1.96	0.050	.9439871	1.000001
belowavg_income	.9524515	.01187	-3.91	0.000	.9294639	.9760077
aboveavg_income	.9473827	.0118878	-4.31	0.000	.9243625	.9709762
preftoleave_strong	.9430425	.0111096	-4.98	0.000	.9215132	.9650747
preftoleave_mod	.9670502	.0128212	-2.53	0.012	.9422396	.992514
perceivedhlth_good	.9524383	.0217609	-2.13	0.033	.91072	.9960675
perceivedhlth_fair	1.052752	.0213966	2.53	0.011	1.011631	1.095544
kerosene	1.00259	.0006328	4.10	0.000	1.00135	1.003831
other_sources1	1.004108	.0015166	2.71	0.007	1.00114	1.007086
_cons	21.09159	1.062693	60.51	0.000	19.1079	23.28122

Source: Own calculations using NIDS dataset.

In modelling the comprehensive digital index, the regression model with an F Statistic [27, 5815] of 19.53, and a p-value of 0.0000 demonstrating the overall statistical significance of the model, explained 21.81 % of the variation in the comprehensive digital index based on included feature variables. When compared with the R-squared value in Waves 1 and 2 for the same index, a small improvement is observed for wave 3 in model explanatory power. Furthermore, the influence of skills, socioeconomic characteristics (population grouping, household income, household assets, household infrastructure, occupational prestige and income status) and exclusion (social support, access to services and health services) can be seen to be positively associated with this index.

Table 22: Modelling the Communication Asset Index Wave 3

Survey: Linear regression

Number of strata	= 53		Number of obs	= 5,894
Number of PSUs	= 5,894		Population size	= 15,481,030
			Design df	= 5,841
			F(31, 5811)	= 52.79
			Prob > F	= 0.0000
			R-squared	= 0.6417

comms_asset_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.gender_var	1.22636	.1189932	2.10	0.036	1.013933	1.483292
income_positive	1.295634	.0702103	4.78	0.000	1.165055	1.440849
publicwat_proximate	.9292542	.0202306	-3.37	0.001	.890429	.9697722
publicwat_spring	.8973501	.0204114	-4.76	0.000	.8582153	.9382696
lowcosthousing_thatch	1.150458	.0459977	3.51	0.000	1.063729	1.244258
lowcosthousing_informalshack2	1.09883	.0290989	3.56	0.000	1.043241	1.157382
sanitation_flush2	.8192581	.0356097	-4.59	0.000	.7523414	.8921267
middle_school	1.257251	.0732474	3.93	0.000	1.121556	1.409364
lowcosthousing_mud	1.067124	.0321969	2.15	0.031	1.005837	1.132146
retail_matric	1.180207	.0623452	3.14	0.002	1.064103	1.308979
modernhousing_brick	1.128268	.0609666	2.23	0.026	1.014863	1.254344
primaryedu_workers	.4083959	.0533191	-6.86	0.000	.3161751	.5275153
sanitation_pitlatrine	.9308385	.0215624	-3.09	0.002	.8895136	.9740832
publicwat_borehole	.9312346	.0189478	-3.50	0.000	.894821	.96913
lowcosthousing_retirement2	.95648	.0153033	-2.78	0.005	.9269455	.9869555
economically_active	.8501492	.0458266	-3.01	0.003	.7648958	.9449047
socialsupport	.8918932	.0233035	-4.38	0.000	.8473599	.9387669
well_to_do	1.118534	.0244545	5.12	0.000	1.071607	1.167516
middle_income	1.620147	.0394627	19.81	0.000	1.544603	1.699385
rental_access	.9464463	.0176516	-2.95	0.003	.9124676	.9816903
service_access	.8920236	.0199095	-5.12	0.000	.8538353	.93192
well_to_do2	1.083591	.0414117	2.10	0.036	1.005375	1.167892
lowlevelinst_acc	.3977295	.0525074	-6.98	0.000	.307037	.5152107
belowavg_income	1.09539	.030107	3.31	0.001	1.037931	1.15603
preftoleave_strong	1.191962	.035689	5.86	0.000	1.124012	1.264019
muslim_hindu	1.136335	.0491978	2.95	0.003	1.043868	1.236992
labourmkt_activegen	1.06612	.0311254	2.19	0.028	1.006816	1.128918
unemployed_discouraged	.8649143	.0383776	-3.27	0.001	.7928593	.9435177
chronic_disease2	.9823778	.0049476	-3.53	0.000	.9727265	.9921249
perceivedhlth_good	1.158583	.0611883	2.79	0.005	1.044631	1.284964
none2	.9683551	.0096607	-3.22	0.001	.9496006	.98748
_cons	1.355374	.1676287	2.46	0.014	1.063563	1.72725

Source: Own calculations using NIDS dataset.

In modelling the communication asset index presented in Table 22, the MLR model with an F Statistic [31, 5811] of 52.79 and overall significance shown by a p-value of 0.0000, explained 64.17 % of the variation in the communication asset index based on the included explanatory variables in the model. In the analysis of the communication asset index, the influence of population grouping when compared with Wave 1 and Wave 2 has subsided while access to income has become a key contributing variable (income_positive—1.30, middle-income status 1.62). This is significant since multiple studies confirm the emergence of the black middle class during this period spurred by access to education and training and growing income. In this strand a study compared empirical estimations of class such as occupational skills measures, vulnerability indicator, income polarisation and subjective social status and reported considerable variation among the black middle class depending on empirical conceptualisation however, the study concluded the force of the emerging middle-class n racial integration and social cohesion (Burger, Steenekamp, *et al.*, 2015). Another study argues that the evolving black middle class demonstrated tendencies towards higher-order needs and showed substantial intra-class differences amongst the South African middle class (Mattes, 2015). An empirical study argues heterogeneity among the South African Black middle class and differentiates a large growing securely established middle class with consumption patterns similar to the White middle class and another group with weaker productive characteristics with economic vulnerability as a driver of consumption patterns (Burger, Louw, *et al.*, 2015). The model results in Table 22, shows characteristics similar to those observed in these studies such as income-related and socioeconomic characteristics as reducing the racial disparities in access to communication assets.

The modelling of advanced computing skills index presented in Table 23 shows that a statistically significant MLR model (F Statistic [43, 5799] of 37.65 and p-value of 0.0000), explained 60.43 % of the variation in the response variable-based on included feature variables. Regarding advanced computing skills, a racial profile exists through the factors are quite small when compared to earlier waves of the data. Compared to being in the African population group, the advanced computing skills index increases by 1.31 for Coloureds, 2.11 for Indians and 2.93 for Whites. Thus, racial characteristics continue to shape the accumulation of advanced computing skills. Socioeconomic characteristics (household assets [1.07], infrastructure [1.04], housing type [1.04]), social exclusion (labour market access [1.02], social institutions [1.02], household size [1.08], occupational prestige [1.40], household income [1.06]) and skills profile (medium-skilled work [1.26], communication skills [1.22], advanced skills [2.38]), are positively associated with the advanced computing skills index.

Table 23: Modelling the Computing Skills Index A Wave 3

Survey: Linear regression

Number of strata	= 53		Number of obs	=	5,894
Number of PSUs	= 5,894		Population size	=	15,481,030
			Design df	=	5,841
			F(43, 5799)	=	37.65
			Prob > F	=	0.0000
			R-squared	=	0.6043

comp_lita_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
population_grp						
2	1.310688	.1341077	2.64	0.008	1.072476	1.601811
3	2.109759	.6066073	2.60	0.009	1.200717	3.707019
4	2.927778	.5837919	5.39	0.000	1.980503	4.328135
medskills_comm	1.262024	.0406812	7.22	0.000	1.184742	1.344348
lowskills_extprcomp	1.198339	.0305927	7.09	0.000	1.139842	1.259838
comms_skills	1.22107	.0256652	9.50	0.000	1.171779	1.272434
lowskills_poorlangcomp	1.161081	.0230503	7.52	0.000	1.116762	1.207159
highskills_complit	2.384816	.0815527	25.42	0.000	2.230183	2.55017
hsehold_asset_index	1.076269	.0204367	3.87	0.000	1.036942	1.117088
publicwat_proximate	.9364779	.0159167	-3.86	0.000	.9057894	.9682062
publicwat_spring	1.043642	.017863	2.50	0.013	1.009205	1.079255
smallhsehld	1.081625	.030301	2.80	0.005	1.023825	1.142687
lowcosthousing_corr	.9499159	.0202631	-2.41	0.016	.9110118	.9904814
lowcosthousing_wood	1.042413	.0198686	2.18	0.029	1.004182	1.082099
productiveasset_index	.924087	.0281307	-2.59	0.010	.8705537	.9809123
socialservices_proff	.8416647	.0369896	-3.92	0.000	.7721872	.9173935
retail_matric	1.418464	.0582783	8.51	0.000	1.308697	1.537438
largehousehold	.9304176	.0171286	-3.92	0.000	.8974379	.9646092
economically_inactive1	1.663843	.1036813	8.17	0.000	1.472514	1.880033
nottraditional_dwell	1.104318	.0306014	3.58	0.000	1.045928	1.165968
manufacturing_work	1.278213	.0452853	6.93	0.000	1.19245	1.370145
well_to_do1	.912672	.0320474	-2.60	0.009	.8519608	.9777095
artisans_transcomms	.9281166	.0285929	-2.42	0.015	.873723	.9858965
artisans2	1.11757	.040901	3.04	0.002	1.040198	1.200697
lowcosthousing_stone	.882574	.0274569	-4.02	0.000	.8303568	.9380748
lowcosthousing_backroom	1.182012	.0320127	6.17	0.000	1.120892	1.246465
economically_active	1.113607	.0511661	2.34	0.019	1.017687	1.218568
govservices_access	.9619862	.0111998	-3.33	0.001	.9402792	.9841944
labmkt_active	.7212887	.02333	-10.10	0.000	.6769731	.7685052
sedentary	.8724257	.0344456	-3.46	0.001	.8074467	.9426339
middle_income	1.061665	.0161569	3.93	0.000	1.030459	1.093815
well_to_do2	1.135342	.0318143	4.53	0.000	1.074656	1.199455
employed_educated	1.406389	.0693916	6.91	0.000	1.276728	1.549219
belowavg_income	.9279872	.0190372	-3.64	0.000	.8914077	.9660677
muchbelowavg_income	.9064139	.0188223	-4.73	0.000	.8702562	.9440738
aboveavg_income	.9354832	.0175068	-3.56	0.000	.9017853	.9704403
discouraged_unemployed	1.115541	.035912	3.40	0.001	1.047316	1.188211
economically_inactive	.837288	.0371363	-4.00	0.000	.7675622	.9133477
labourmkt_activegen	1.027117	.0196676	1.40	0.162	.9892761	1.066406
chronic_disease1	.9564563	.0126264	-3.37	0.001	.9320214	.9815317
chronic_disease4	1.048378	.0134311	3.69	0.000	1.022376	1.075041
none2	.9676744	.0061899	-5.14	0.000	.9556158	.9798852
other_sources2	1.009825	.0021035	4.69	0.000	1.00571	1.013957
_cons	1.068161	.069015	1.02	0.308	.9410838	1.212398

Source: Own calculations using NIDS dataset.

Table 24:Modelling the Computer Skills Index B Wave 3

Survey: Linear regression

Number of strata = 53
Number of PSUs = 5,894

Number of obs = 5,894
Population size = 15,481,030
Design df = 5,841
F(42, 5800) = 118.02
Prob > F = 0.0000
R-squared = 0.7243

comp_litb_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
population_grp						
2	1.412025	.1014503	4.80	0.000	1.226516	1.625593
3	3.096933	.5239339	6.68	0.000	2.222783	4.314858
4	2.065941	.2172138	6.90	0.000	1.68114	2.538822
medskills_comm	2.179371	.0466616	36.39	0.000	2.089791	2.272792
lowskills_extprcomp	1.328467	.0241216	15.64	0.000	1.282012	1.376606
comms_skills	1.176291	.0192268	9.93	0.000	1.139197	1.214593
lowskills_poorlangcomp	1.191948	.0174184	12.02	0.000	1.158286	1.226588
highskills_complit	.5767402	.0120631	-26.31	0.000	.5535702	.6008799
publicwat_spring	.9517566	.0112731	-4.17	0.000	.9299116	.9741146
publicwat_distantstream	1.03142	.0113416	2.81	0.005	1.009424	1.053895
middle_school	.8643412	.0172394	-7.31	0.000	.8311977	.8988062
socialservices_cert	1.149247	.0305973	5.22	0.000	1.090803	1.210822
socialservices_proff	1.162963	.0308599	5.69	0.000	1.104012	1.225061
retail_matric	.584988	.0200029	-15.68	0.000	.5470602	.6255453
hsehld_employed	.787706	.0232456	-8.09	0.000	.7434291	.83462
modernhousing_brick	1.045588	.0168701	2.76	0.006	1.013034	1.079188
economically_inactive1	.6215594	.0275487	-10.73	0.000	.5698334	.6779808
manufacturing_work	.6858528	.0201769	-12.82	0.000	.6474177	.7265698
large_hsehldpoor	.9155915	.014594	-5.53	0.000	.8874242	.9446528
lowcosthousing_thatch1	1.054384	.0276666	2.02	0.044	1.001519	1.11004
well_to_do1	1.05861	.023463	2.57	0.010	1.013599	1.10562
notpvthsehld_work	1.234223	.0276662	9.39	0.000	1.181161	1.289668
artisans_transcomms	1.141995	.0216845	6.99	0.000	1.100267	1.185306
artisans2	.8947549	.0199133	-5.00	0.000	.8565569	.9346564
artisans_middleclass	.9539995	.014269	-3.15	0.002	.9264331	.9823862
lowcosthousing_stone	1.183335	.0215058	9.26	0.000	1.141918	1.226255
lowcosthousing_backroom	.7452603	.0174196	-12.58	0.000	.711882	.7802037
labmkt_active	1.163121	.0345886	5.08	0.000	1.097253	1.232943
sedentary	.8714464	.0239018	-5.02	0.000	.8258274	.9195854
service_access	1.019615	.0078125	2.54	0.011	1.004414	1.035046
lowlevelinst_acc	1.096929	.0183582	5.53	0.000	1.061524	1.133515
belowavg_income	.9440135	.0121723	-4.47	0.000	.9204502	.9681799
muchbelowavg_income	.961947	.0142402	-2.62	0.009	.9344321	.9902721
aboveavg_income	.9517416	.010508	-4.48	0.000	.9313634	.9725657
preftoleave_strong	.9773468	.0117964	-1.90	0.058	.9544929	1.000748
preftoleave_mod	.9698081	.0123241	-2.41	0.016	.9459468	.9942712
other_religions	.981399	.0099696	-1.85	0.065	.9620483	1.001139
jobsecurity_low	1.070767	.0165152	4.43	0.000	1.038876	1.103637
unemployed_strict	.6969721	.026043	-9.66	0.000	.6477433	.7499424
unemployed_discouraged	1.06942	.0274238	2.62	0.009	1.016988	1.124555
chronic_disease1	.9734768	.0114342	-2.29	0.022	.9513176	.9961522
chronic_disease2	1.007814	.002845	2.76	0.006	1.002252	1.013406
_cons	.7700672	.0223087	-9.02	0.000	.7275525	.8150663

Source: Own calculations using NIDS dataset.

In modelling the basic computing skills index, the model explained 72.43% of the overall variation in the dependent variable. The influence of population grouping continued to influence the basic computing skills index, showing that compared to being in the African population group, being Coloured increases the basic computing skills index by 1.41, being Indian by 3.09 and being White by 2.07. In Table 24, the coefficients of low to middle-skills can be seen to be above 1 (medskills_comm [2.17], lowskills_extprcomp [1.32], comms_skills [1.18], lowskills_prlangcomp [1.19]) showing that basic computing skills are associated with low to middle-skilled occupations. Some occupations can also be seen to be positively associated with basic computing skills index (such as certificate level social work [1.15] and professional social work [1.16], artisans—transport [1.14]), the influence of household characteristics and access to services (service_access [1,01]) and access to social institutions (lowlevelinst_acc [1.09]). Increasing access to public services which encourage skills development and access to public learning facilities and environments can positively improve access to basic computing skills among Africans.

In modelling the low access to digital technology index, the MLR model with an F Statistic [12, 5830] of 4.71 and model p-value of 0.0000 explained 3.03 % of the variation in the low access to digital technology index, based on included explanatory variables. When compared with the modelling for Wave 1 and 2, the dataset does not seem to have attributes that can be instrumental in significantly explaining low access to digital technologies. In the model, socioeconomic characteristics explaining household-level characteristics are important predictors. Household infrastructure services (sanitation facilities [1.15], low-cost structures [1.17], distant water sources [1.12], low-cost stone housing [1.06], which are consistent with poorly serviced marginalized areas in rural and remote regions shows high association with low access to digital technologies. These characteristics have been explained in other studies as being responsible for the persisting rural digital divide (Joseph and Andrew, 2007) and undermining prospects for women empowerment through access to ICTs (Jiyane, 2021) since the supporting infrastructures are not available in such locations. In an empirical paper, the authors found low access to digital technologies to be associated with women's labour market participation (Omotoso Kehinde Oluwaseun, Adesina Jimi, and Adewole Ololade G., 2020).

Table 25: Modelling the index for Low Access to Digital Technologies.

Survey: Linear regression

Number of strata = 53	Number of obs = 5,894
Number of PSUs = 5,894	Population size = 15,481,030
	Design df = 5,841
	F(12, 5830) = 4.71
	Prob > F = 0.0000
	R-squared = 0.0303

low_dig_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf. interval]	
4.population_grp	.5630356	.0973916	-3.32	0.001	.4011141	.7903213
sanitation_pipedwater	1.153673	.0331524	4.97	0.000	1.090479	1.22053
lowcosthousing_thatch	1.168775	.0467164	3.90	0.000	1.08069	1.26404
publicwat_distantstream	.9153813	.0203827	-3.97	0.000	.8762832	.9562237
publicwat_distantwat	1.127221	.0249958	5.40	0.000	1.07927	1.177303
productiveasset_index	.9521331	.0197288	-2.37	0.018	.9142323	.9916051
publicwat_distantdam	.9290073	.0164671	-4.15	0.000	.8972801	.9618563
nottraditional_dwell	1.066635	.02866	2.40	0.016	1.011904	1.124325
artisans2	.9436746	.0209933	-2.61	0.009	.9034046	.9857397
lowcosthousing_wood	.9546998	.0105265	-4.20	0.000	.9342853	.9755603
lowcosthousing_stone	1.061687	.0303329	2.10	0.036	1.003858	1.122848
rental_access	.9576776	.0163009	-2.54	0.011	.926249	.9901725
_cons	1.449833	.1032004	5.22	0.000	1.261003	1.66694

Source: Own calculations using NIDS dataset.

5.10.4 Regression Analysis for NIDS Wave 4

In modelling the digital index in wave 4, the individual multiple linear regression models are explained focusing on the regressions explanatory power with the feature variables being explained in their influence on the model and their meaning in applying the results of the model. A comparative analysis with previous results in Wave 1, 2 and 3 is undertaken so that the results can be placed in the context of trends in previous waves of the NIDS data.

Table 26: Modelling the Comprehensive Digital Index Wave 4.

Survey: Linear regression

Number of strata = 53
Number of PSUs = 9,397

Number of obs = 9,397
Population size = 24,959,398
Design df = 9,344
F(48, 9297) = 19.39
Prob > F = 0.0000
R-squared = 0.1742

comp_dig_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
4.population_grp	.5856179	.0655035	-4.78	0.000	.4703185	.7291833
secondary_instedu	1.423721	.116784	4.31	0.000	1.212255	1.672075
primaryedu_skills	.6382093	.0806056	-3.56	0.000	.4982448	.817492
retail_matric	1.203145	.0466428	4.77	0.000	1.115102	1.298138
financial_skills	.8336513	.0267071	-5.68	0.000	.7829094	.8876819
transcommskills	.8800089	.0194974	-5.77	0.000	.8426078	.9190701
energyindustry_tt	1.100381	.0130057	8.09	0.000	1.07518	1.126173
household_work	.936355	.0202624	-3.04	0.002	.8974669	.9769282
skilledagricwork	1.00616	.0029832	2.07	0.038	1.000329	1.012024
labmkt_active	1.161421	.0456217	3.81	0.000	1.075348	1.254382
sedentary_inactive	.9262594	.0233523	-3.04	0.002	.8815964	.973185
middle_income	.9297823	.0076342	-8.87	0.000	.9149374	.9448681
employed_educated	1.146089	.0538494	2.90	0.004	1.045248	1.25666
loweduc_level	.6518548	.0701613	-3.98	0.000	.5278632	.8049712
university_instaccess	.9439148	.0124242	-4.39	0.000	.9198722	.9685859
preftostay_leave	.965265	.0116472	-2.93	0.003	.9427017	.9883683
publicinfr_access	1.017639	.0071439	2.49	0.013	1.003731	1.031739
preftoleave_mod	.9677267	.0115774	-2.74	0.006	.9452965	.9906891
wealthy_class	.9425228	.011659	-4.79	0.000	.9199434	.9656564
muslim_religion	.9625177	.0171715	-2.14	0.032	.9294395	.9967732
hinduism_religion	.9618058	.0130562	-2.87	0.004	.9365502	.9877424
hsehld_assets1_index	1.158818	.0117055	14.59	0.000	1.136098	1.181992
wateraccess_piped	1.051243	.012874	4.08	0.000	1.026307	1.076784
hsehld_assets2_index	1.066042	.0168355	4.05	0.000	1.033546	1.099559
modernhousing_tiled	1.036914	.0139388	2.70	0.007	1.009948	1.0646
householdsize_med	1.051094	.0128967	4.06	0.000	1.026116	1.076681
informaldwell_plastic	.980702	.0068688	-2.78	0.005	.9673295	.9942592
secondaryedu_skills1	.8164968	.0723936	-2.29	0.022	.6862368	.9714823
modernhousing_apartment	.9581282	.0136888	-2.99	0.003	.9316675	.9853404
lowcosthousing_wattle	.945128	.0172678	-3.09	0.002	.9118783	.9795901
lowcosthousing_wood	1.027928	.0135792	2.09	0.037	1.001652	1.054894
wholesale_skills	.7560219	.0340469	-6.21	0.000	.6921435	.8257957
nothousehold_work	1.11583	.0379996	3.22	0.001	1.043774	1.19286
financialskills_vocational	1.269333	.0541407	5.59	0.000	1.167521	1.380024
energy_caravan	.9424207	.0099117	-5.64	0.000	.9231904	.9620515
constructionskills	.9567481	.0164553	-2.57	0.010	.9250298	.9895539
poorhousing_conditions	1.035847	.011785	3.10	0.002	1.013002	1.059208
miningquarrying_skills	1.05147	.0184917	2.85	0.004	1.01584	1.08835
technicalskills	.9127079	.0165587	-5.03	0.000	.8808197	.9457505
transport_commskills	1.212141	.0414667	5.62	0.000	1.133523	1.296212
retirement_unit	1.032461	.0119136	2.77	0.006	1.00937	1.05608
employed_secure	.9058057	.0333654	-2.69	0.007	.8427077	.9736283
economically_inactive	1.072978	.0315877	2.39	0.017	1.012812	1.136718
nosecure_employment	.9537816	.0157625	-2.86	0.004	.9233788	.9851854
independently_employed	.8877183	.0380981	-2.78	0.006	.8160927	.9656302
basiccomp_commskills	1.047577	.0161031	3.02	0.003	1.016482	1.079622
communicationskills_good	1.023925	.0108248	2.24	0.025	1.002925	1.045366
highlyskilled_complit	1.06172	.0148017	4.30	0.000	1.033099	1.091135
_cons	12.02625	.3920572	76.29	0.000	11.28177	12.81985

Source: Own calculations using NIDS dataset.

In modelling the comprehensive digital asset index, the MLR was statistically significant with an F Statistic [48, 9297] of 19.39 and a model p-value of 0.0000 and explained 17.42 % of the variation in the response variable. Among the explanatory variables having a strong association for each 1-unit change in their value are socioeconomic characteristics (occupation—retail_matric [1.20], industry workers [1.1], employment status [1.14], household assets [1.15] and household infrastructure), social exclusion/inclusion (labour market participation [1.16], public infrastructure access [1.02]) and skills (basic computing skills [1.05], communication skills [1.02] and highly skilled individuals [1.06]. While these variables are significant, they continue to contribute to explaining a small proportion of the variation in the comprehensive digital index.

In modelling the communication asset index, a statistically significant MLR model with an F Statistic [55, 9290] of 101.26 and a model p-value of 0.0000, explained 71.30 % of the variation in the communication asset index which modelled access to advanced digital technologies. Comparing the demographic variables in this model with previous models in Waves 1-3, it can be noted in Table 27 that the influence of race is strong for every unitary change in the explanatory variables. With Africans as the reference group, being Coloured increases the communication asset index by 1.35 points, being Indian by 3.06 points and being White by 1.75 points, demonstrating that African continue to trail other population groups in access to advanced communication assets. Educational institution access (Secondary education [2.43]) and high skills (highly skilled [2.75]) have an association with the communication asset index. Generally, the positive influence of socioeconomic characteristics, social exclusion and skills continue to influence the communication asset index as in previous waves of the data. A study conducted in 2015, and adjacent to the time of the publication of NIDS Wave 4 data, 2014/2015 (Brophy *et al.*, 2018), found through an empirical investigation the existence of considerable gaps between population groups and educational levels as influencing internet and computer usage (Bornman, 2016). The results of the model on the communication asset index also highlight an important aspect in the extant literature that while infrastructure development and creation of appropriate policy environment has been progressing in South Africa, important factors not related to infrastructure but aligned with individual dynamics have exhibited an impact on individual ICTs usage and that there are existing digital divides within the South African population (Bornman, 2016). In this study, these dynamics are explained to be socioeconomic characteristics, social exclusion/inclusion and skills profile of individuals.

Table 27: Modelling the Communication Asset Index for Wave 3.

Survey: Linear regression

Number of strata =	53	Number of obs =	9,397
Number of PSUs =	9,397	Population size =	24,959,398
		Design df =	9,344
		F(55, 9290) =	101.26
		Prob > F =	0.0000
		R-squared =	0.7130

comms_asset_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.gender_var	.8954396	.0377743	-2.62	0.009	.8243725	.9726332
population_grp						
2	1.352251	.1055724	3.87	0.000	1.160364	1.575871
3	3.061371	.6241318	5.49	0.000	2.052846	4.565367
4	1.748135	.2648791	3.69	0.000	1.298923	2.3527
secondary_instedu	2.433824	.1736213	12.47	0.000	2.116212	2.799104
socialskills_cert	.8798068	.0389427	-2.89	0.004	.8066885	.9595525
retail_matric	1.535957	.0624365	10.56	0.000	1.418317	1.663354
financial_skills	.7896061	.0338339	-5.51	0.000	.7259933	.8587928
skilled_plantmachine	.8892104	.0200002	-5.22	0.000	.8508573	.9292923
mining_quarrying	1.19305	.0198534	10.61	0.000	1.154761	1.232609
transcommskills	.8381861	.0269842	-5.48	0.000	.7869256	.8927857
energyindustry_tt	1.143296	.0205505	7.45	0.000	1.103714	1.184297
household_work	.8726632	.0218839	-5.43	0.000	.8308033	.9166323
servicesales_workers	1.0469	.0108226	4.43	0.000	1.025899	1.068331
perceivedhealth_poor	1.021836	.008132	2.71	0.007	1.006019	1.037901
chronicdiseases_tbheart	1.011945	.0057147	2.10	0.036	1.000805	1.023209
middle_income	1.023893	.0122762	1.97	0.049	1.00011	1.048242
capmkt_access	1.033525	.0127855	2.67	0.008	1.008764	1.058894
loweduc_level	2.037082	.1225818	11.82	0.000	1.810425	2.292114
university_instaccess	1.074489	.023613	3.27	0.001	1.029185	1.121787
belowavg_income	.9380953	.0125266	-4.79	0.000	.9138591	.9629743
unemployed_discouraged	1.133967	.026733	5.33	0.000	1.082756	1.187599
hsehld_assets1_index	1.041755	.0109488	3.89	0.000	1.020512	1.063439
hsehld_assets2_index	1.150136	.0271202	5.93	0.000	1.098185	1.204545
modernhousing_tiled	1.064344	.0179897	3.69	0.000	1.029658	1.100198
educated_wealthy	1.070436	.0249005	2.93	0.003	1.022722	1.120377
socialservices_cert	1.202769	.0525845	4.22	0.000	1.103985	1.310392
secondaryedu_skills1	.2714331	.0260728	-13.58	0.000	.224848	.3276699
unemployed_nteducated	1.192199	.0669664	3.13	0.002	1.067899	1.330967
modernhousing_apartment	.9417168	.0193779	-2.92	0.004	.9044877	.9804782
lowcosthousing_wattle	.963486	.0114745	-3.12	0.002	.941254	.9862431
lowcosthousing_mudcmnt	1.078437	.0137739	5.91	0.000	1.051772	1.105777
wholesale_skills	.547635	.0294812	-11.19	0.000	.4927901	.6085838
nothousehold_work	1.232068	.0526173	4.89	0.000	1.133126	1.33965
financialskills_vocational	1.406399	.0875658	5.48	0.000	1.244812	1.588961
sanitation_buckettoi	1.037193	.0201126	1.88	0.060	.9985081	1.077377
discouraged_unemployed	.8483317	.0249992	-5.58	0.000	.8007163	.8987787
constructionskills	.8986188	.0177955	-5.40	0.000	.8644041	.9341877
wateraccess_mobilewater	1.045648	.0156517	2.98	0.003	1.015413	1.076783
poorhousing_conditions	1.03752	.0136347	2.80	0.005	1.011134	1.064594
householdsize_exlarge	.8730683	.0148228	-8.00	0.000	.8444905	.9026132
technicalskills	.8427086	.0243755	-5.92	0.000	.7962566	.8918705
transport_commskills	1.194126	.0530919	3.99	0.000	1.09446	1.302867
retirement_unit	1.052132	.0113867	4.70	0.000	1.030047	1.074691
employed_secure	.7787548	.017194	-11.33	0.000	.7457699	.8131987
economically_inactive	.8302685	.0181611	-8.50	0.000	.7954211	.8666425
nosecure_employment	.8905434	.0128416	-8.04	0.000	.8657235	.9160749
independently_employed	1.126365	.0479361	2.80	0.005	1.036212	1.224361
casual_work	1.068454	.0132279	5.35	0.000	1.042837	1.094701
basiccomp_commskills	1.27595	.0292622	10.63	0.000	1.21986	1.334619
communicationskills_good	1.230704	.0196402	13.01	0.000	1.192801	1.269812
communicationskills_poor	1.15134	.0123758	13.11	0.000	1.127334	1.175856
communicationskills_mod	1.15936	.0138539	12.37	0.000	1.132518	1.186837
highlyskilled_complit	2.749782	.0691374	40.23	0.000	2.617543	2.888701
medlevel_skills	1.232934	.029118	8.87	0.000	1.177157	1.291353
_cons	.7667078	.0277623	-7.34	0.000	.7141741	.8231059

Source: Own calculations using NIDS dataset.

Table 28: Modelling the Computing Skills Index A Wave 4

Survey: Linear regression

Number of strata =	53	Number of obs =	9,397
Number of PSUs =	9,397	Population size =	24,959,398
		Design df =	9,344
		F(41, 9304) =	46.08
		Prob > F =	0.0000
		R-squared =	0.5988

comp_lita_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
secondary_instedu	.3572622	.0399552	-9.20	0.000	.2869319	.4448313
primaryedu_skills	15.72951	4.03179	10.75	0.000	9.517146	25.99702
financial_skills	1.192503	.0334814	6.27	0.000	1.128646	1.259974
mining_quarrying	1.093359	.0263906	3.70	0.000	1.042832	1.146334
transcommskills	1.069553	.0249993	2.88	0.004	1.021655	1.119697
household_work	1.084061	.0229115	3.82	0.000	1.040067	1.129916
clericaladmin_work	1.043723	.0142747	3.13	0.002	1.016113	1.072083
servicesales_workers	1.103986	.0337948	3.23	0.001	1.039689	1.172259
labmkt_active	.3808898	.0359365	-10.23	0.000	.3165769	.4582681
well_to_do	1.109091	.0227383	5.05	0.000	1.065402	1.15457
sedentary_inactive	1.667744	.0953106	8.95	0.000	1.490999	1.86544
middle_income	1.39972	.0249272	18.88	0.000	1.3517	1.449445
capmkt_access	1.283959	.0265049	12.11	0.000	1.233041	1.33698
employed_educated	.2118618	.0280278	-11.73	0.000	.163467	.274584
loweduc_level	11.67036	2.638894	10.87	0.000	7.491803	18.17952
university_instaccess	1.373755	.0430487	10.13	0.000	1.291909	1.460785
belowavg_income	1.080095	.0249019	3.34	0.001	1.032368	1.130028
muchbelowavg_income	1.195407	.0308985	6.91	0.000	1.136348	1.257536
preftostay_leave	1.084199	.0274852	3.19	0.001	1.031639	1.139437
publicinfr_access	.8602579	.0134792	-9.61	0.000	.8342373	.88709
noreligion	1.078522	.0286642	2.84	0.004	1.023773	1.1362
preftoleave_mod	1.106859	.0271024	4.15	0.000	1.054988	1.161281
unemployed_discouraged	2.14738	.184935	8.87	0.000	1.813815	2.542289
other_religion	1.169817	.0478144	3.84	0.000	1.079747	1.2674
jewish_religion	1.059937	.0198159	3.11	0.002	1.021797	1.099501
hsehld_assets1_index	1.120122	.0229769	5.53	0.000	1.075975	1.166079
lowcosthousing_trad	1.059216	.0198868	3.06	0.002	1.020942	1.098925
educated_wealthy	.9132166	.0310488	-2.67	0.008	.8543379	.976153
wateraccess_onsite	.9359439	.0196989	-3.15	0.002	.8981154	.9753657
socialservices_cert	1.536322	.0652178	10.12	0.000	1.413656	1.669633
secondaryedu_skills1	1.643586	.1972591	4.14	0.000	1.299033	2.079528
modernhousing_flat	.904144	.0295296	-3.09	0.002	.8480735	.9639216
wholesale_skills	1.253246	.0541761	5.22	0.000	1.151424	1.364072
notmanufacturing	.8848576	.0279721	-3.87	0.000	.8316904	.9414236
poorhousing_conditions	1.053487	.0253974	2.16	0.031	1.004861	1.104466
lowcosthousing_flatlet	.9173198	.0314428	-2.52	0.012	.85771	.9810724
employed_secure	1.6068	.1303872	5.84	0.000	1.370504	1.883837
economically_inactive	.4980465	.033366	-10.40	0.000	.4367545	.5679399
nosecure_employment	1.189471	.0401748	5.14	0.000	1.11327	1.270888
independently_employed	4.086897	.5116561	11.24	0.000	3.197528	5.223638
unemployed_disc	.4853615	.0404471	-8.67	0.000	.4122133	.5714899
_cons	1.262734	.0864707	3.41	0.001	1.104117	1.444139

Source: Own calculations using NIDS dataset.

In modelling the advanced computing skills index, the multiple linear regression model with an F Statistic [41, 9304] of 40.08 and an associated model p-value of 0.0000, explained 59.88 % of the variation in the response variable. Comparing the results in Table 28 with the same results for Wave 3 of the NIDS data presented in Table 23, it can be noticed that the influence of the population grouping variable on advanced computing skills is absent. The large coefficients on individuals exhibiting low education levels yet highly experienced are significant (primaryedu_skills [15.73], lowedu_level [11.67], unemployed_discouraged [2.15] and independently_employed [4.09]). For all other explanatoy variables, it can be seen that for every 1 unit increase in the explanatory variable, there is at least a 1 unit increase for skills (financial_skills [1.19], mining_quarrying [1.09], transcommskills [1.07], clericaladmin_work [1.04], servicesales_workers [1.10], socialservices_cert[1.54], secondaryedu_skills[1.64]), socioeconomic characteristics (well_to_do[1.11], sedentary_inactive[1.67], middle_income[1.40], hsehld_asset_index[1.12], poorhousing_conditions[1.05]) and social exclusion/inclusion (university_access[1.37], captmkt_access[1.28], noreligion[1.07], other_religion[1.17], jewish_religion[1.05], employed_secure[1.61], nosecure_employment[1.19]). Thus, the results show the continued influence of skills, socioeconomic characteristics and social exclusion/inclusion.

The findings presented in Table 28 show deviation from the previous result for the advanced computing skills index in Waves 1-3, as they show the high influence of low skills, low education and poor socioeconomic conditions such as poor housing conditions and inactive people being positively associated with the advanced computing skills index. These results may be attributable to the government's training policies focusing on education and advanced skills, as well as increased enrolment in tertiary education among youths, through education financing and assistance or other forms of empowerment, which have removed socioeconomic and other barriers to accessing advanced skills, education and training (Mishra, 2017).

In modelling the basic computing skills index, the MLR model with an F Statistic [61, 9284] of 256.04 and a model p-value of 0.0000 explained 82.21% of the overall variation in the dependent variable. The influence of the race variable can be observed as comparing the African population group with other groups shows that being Coloured as compared to being African, increases the basic computing skills index by 1.36, being Indian by 2.68 and being White by 1.75. The results in Table 29 shows a strong influence of secondary education and basic computing and communication skills on the index with 2.03 and 2.21 coefficients respectively. The racial dynamics aligned with a dual education profile in South Africa reflects these outcomes among population groups (Branson and Leibbrandt, 2013; Kimani, 2015). The influence on skills profiles of individuals is noticeable with the large coefficients on good communication skills [1.33], poor communication skills [1.21] and moderate communication skills [1.22].

Table 29: Modelling the Basic Computing Skills Index Wave 4

Survey: Linear regression

Number of strata = 53		Number of obs =	9,397
Number of PSUs = 9,397		Population size =	24,959,398
		Design df =	9,344
		F(61, 9284) =	256.04
		Prob > F =	0.0000
		R-squared =	0.8221

comp_litb_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
population_grp						
2	1.355197	.0662227	6.22	0.000	1.231409	1.491428
3	2.681671	.3088076	8.57	0.000	2.139798	3.360765
4	1.753508	.1248114	7.89	0.000	1.525151	2.016056
secondary_instedu	.6658975	.0139306	-19.44	0.000	.6391427	.6937722
socialskills_cert	1.151296	.0136911	11.85	0.000	1.124769	1.178449
financial_skills	1.118659	.0219088	5.73	0.000	1.076527	1.16244
skilled_plantmachine	1.030953	.0117175	2.68	0.007	1.008239	1.05418
mining_quarrying	.8399863	.0063602	-23.03	0.000	.827611	.8525467
transcommskills	1.114722	.0183483	6.60	0.000	1.079329	1.151275
crafts_tradetested	1.06163	.016993	3.74	0.000	1.028837	1.095468
energyindustry_tt	.9356093	.0090224	-6.90	0.000	.9180896	.9534634
household_work	1.080399	.0078011	10.71	0.000	1.065215	1.0958
elementary_occupations	1.071219	.0097262	7.58	0.000	1.052323	1.090455
plantmachine_skillsgen	1.017406	.0048059	3.65	0.000	1.008028	1.02687
perceivedhealth_vgood	.9859391	.0076614	-1.82	0.068	.9710348	1.001072
well_to_do	1.013075	.0051234	2.57	0.010	1.003082	1.023168
sedentary_inactive	.7304591	.0120282	-19.07	0.000	.7072577	.7544217
middle_income	1.021219	.00603	3.56	0.000	1.009467	1.033108
capmkt_access	.9879779	.0058737	-2.03	0.042	.976531	.9995589
loweduc_level	.7009245	.0243122	-10.24	0.000	.6548513	.7502392
university_instaccess	1.050382	.0095132	5.43	0.000	1.031898	1.069196
belowavg_income	.9175069	.007237	-10.92	0.000	.9034299	.9318032
muchbelowavg_income	.938792	.0067314	-8.81	0.000	.9256892	.9520802
preftostay_leave	.9313665	.00716	-9.25	0.000	.9174367	.9455079
preftostay_indiff	.9325272	.0085858	-7.59	0.000	.9158482	.94951
traditional_auth	.944966	.0068075	-7.86	0.000	.9317156	.9584048
preftoleave_strong	.9634289	.0066226	-5.42	0.000	.9505342	.9764985
noreligion	.9637978	.0062556	-5.68	0.000	.9516132	.9761385
preftoleave_mod	.9532094	.0066716	-6.85	0.000	.9402208	.9663773
wealthy_class	.9467926	.0066746	-7.76	0.000	.9337989	.9599672
unemployed_discouraged	.8574979	.0245918	-5.36	0.000	.8106225	.9070838
jewish_religion	.9847166	.0074123	-2.05	0.041	.9702935	.999354
hsehld_assets1_index	1.03087	.0061495	5.10	0.000	1.018886	1.042996
wateraccess_piped	1.017946	.0075231	2.41	0.016	1.003305	1.0328
socialservices_employed	.7378143	.0130017	-17.25	0.000	.7127634	.7637458
householdsize_med	1.027451	.00775	3.59	0.000	1.012371	1.042756
wateraccess_onsite	.9688508	.0059714	-5.13	0.000	.9572161	.980627
informaldwell_plastic	1.015131	.0044859	3.40	0.001	1.006376	1.023963
secondaryedu_skills1	2.029498	.0857472	16.75	0.000	1.868187	2.204738
unemployed_nteducated	.7898936	.0227531	-8.19	0.000	.7465284	.835778
sanitation_bholecommunal	.980306	.0088983	-2.19	0.028	.9630177	.9979047
modernhousing_apartment	1.043476	.0116255	3.82	0.000	1.020935	1.066515
lowcosthousing_mudcmnt	.9498688	.0059814	-8.17	0.000	.938216	.9616663
financialskills_vocational	.8835478	.0246167	-4.44	0.000	.8365877	.9331439
sanitation_buckettoi	.9263279	.0097332	-7.28	0.000	.9074439	.9456049
energy_caravan	1.033026	.01043	3.22	0.001	1.012782	1.053675
discouraged_unemployed	1.091388	.0166601	5.73	0.000	1.059215	1.124539
constructionskills	1.078724	.0113849	7.18	0.000	1.056636	1.101273
householdsize_exlarge	1.035839	.0088047	4.14	0.000	1.018723	1.053243
technicalskills	1.113278	.0154317	7.74	0.000	1.083436	1.143942
transport_commskills	.9147617	.0214798	-3.79	0.000	.8736109	.9578509
retirement_unit	.9020903	.0163013	-5.70	0.000	.8706956	.9346171
nosecure_employment	.965957	.007153	-4.68	0.000	.9520369	.9800806
independently_employed	.8107516	.0200337	-8.49	0.000	.7724171	.8509887
casual_work	1.042218	.0076372	5.64	0.000	1.027354	1.057296
unemployed_disc	1.062147	.0260756	2.46	0.014	1.012243	1.11451
basiccomp_commskills	2.208959	.0341972	51.19	0.000	2.142932	2.27702
communicationskills_good	1.326777	.0142256	26.37	0.000	1.299183	1.354958
communicationskills_poor	1.208354	.0100275	22.81	0.000	1.188856	1.228171
communicationskills_mod	1.224065	.0108036	22.91	0.000	1.20307	1.245427
highlyskilled_complit	.6353008	.0085171	-33.84	0.000	.6188229	.6522176
_cons	1.089004	.0194696	4.77	0.000	1.0515	1.127845

Source: Own calculations using NIDS dataset.

Table 30: Modelling the Index of Low Access to Digital Technology Wave 4

Survey: Linear regression

Number of strata = 53	Number of obs = 9,397
Number of PSUs = 9,397	Population size = 24,959,398
	Design df = 9,344
	F(7, 9338) = 7.19
	Prob > F = 0.0000
	R-squared = 0.0171

low_dig_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	1.327065	.102574	3.66	0.000	1.140489	1.544164
chronicdisease_diabetes	.9838999	.0054184	-2.95	0.003	.9733357	.9945788
rental_access	.9654362	.0141607	-2.40	0.016	.9380734	.9935971
university_instaccess	.956529	.0174836	-2.43	0.015	.9228641	.991422
noreligion	.9582858	.0203524	-2.01	0.045	.9192098	.9990231
other_religion	.9571056	.013635	-3.08	0.002	.9307479	.9842098
hsehld_assets2_index	1.16762	.050289	3.60	0.000	1.073089	1.270478
_cons	1.079319	.0485	1.70	0.089	.9883157	1.178703

Source: Own calculations using NIDS dataset.

The multiple linear regression model estimating the low access to digital technologies was statistically significant with an F Statistic [7, 9338] of 7.19 and a model p-value of 0.0000 and explained a significantly small 1.71 % of the variation in the response variable. The large coefficient on urban location (2. spatial), when compared with rural location, shows that the measured access to low digital technology access is highly associated with people in urban as opposed to rural areas. The results of the MLR model are presented in Table 30.

5.10.5 Regression Analysis for NIDS Wave 5.

In the regression modelling of variables in Wave 5 of the NIDS, attention was paid to the regression model results, comparisons were also made with previous model results, however, the focus was given much to differences between results of Wave 1 and Wave 5. The results of the multiple regression modelling are presented in Table 31 to Table 35. The results are further compared with findings from other studies in the extant literature and the implications of the results on digital transformation are discussed briefly.

Table 31: Modelling the Comprehensive Digital Index Wave 5

```
Survey: Linear regression

Number of strata =     53                  Number of obs   =      6,237
Number of PSUs   = 6,237                   Population size = 18,600,516
                                           Design df       =      6,184
                                           F(36, 6149)     =      24.80
                                           Prob > F        =     0.0000
                                           R-squared       =     0.2154
```

comp_dig_index	exp(coef.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	.9199824	.0368061	-2.08	0.037	.8505866	.99504
population_grp						
2	.6567002	.0458587	-6.02	0.000	.5726832	.7530431
3	.555932	.1305823	-2.50	0.012	.3507879	.8810461
4	.5686085	.077284	-4.15	0.000	.4356094	.7422144
primaryedu_skills	1.210675	.0681687	3.40	0.001	1.084152	1.351964
lowskilled_mining	1.039074	.0147421	2.70	0.007	1.010573	1.068379
well_to_do	.9487648	.0097245	-5.13	0.000	.9298915	.9680211
social_support1	1.030141	.0115436	2.65	0.008	1.007759	1.053021
labmkt_active1	1.061575	.0150588	4.21	0.000	1.032461	1.09151
educ_access	.9520226	.0148454	-3.15	0.002	.9233607	.9815742
strongprof_leave	.9687726	.0117967	-2.61	0.009	.9459209	.9921764
middle_inc	1.051248	.0096644	5.44	0.000	1.032472	1.070365
educated_rich	1.068792	.0247725	2.87	0.004	1.021316	1.118475
sedentary2	.9644938	.0125184	-2.79	0.005	.9402629	.9893492
employed_educ	.9141659	.0299009	-2.74	0.006	.8573895	.9747021
lowlevels_edu	1.232546	.0662377	3.89	0.000	1.109303	1.369481
below_average_inc	.9734489	.01108	-2.36	0.018	.9519687	.9954137
verylow_income	.9642751	.0137755	-2.55	0.011	.9376449	.9916616
noreligion	.955116	.0096029	-4.57	0.000	.9364752	.9741278
aboveavg_income	.9634774	.0120518	-2.97	0.003	.9401389	.9873952
publicwater_inf	.935418	.0105022	-5.95	0.000	.915055	.9562341
hsehld_assets	1.138167	.0122325	12.04	0.000	1.114438	1.162401
modern_housing	1.048254	.0158005	3.13	0.002	1.017733	1.079691
medsized_hsehld	1.054693	.0162227	3.46	0.001	1.023366	1.08698
employed	.8688378	.0242429	-5.04	0.000	.8225897	.917686
concretewalled_hse	1.041293	.0137037	3.07	0.002	1.014772	1.068506
informaldwelling_shack	1.027647	.0098876	2.83	0.005	1.008446	1.047214
publicwater_inf2	.9408766	.0126309	-4.54	0.000	.9164387	.9659662
not_opensource	1.050134	.0143264	3.59	0.000	1.022422	1.078598
lowcostdwelling_rural2	.9378921	.0185478	-3.24	0.001	.9022277	.9749663
lowpaid_miningwork	.9572613	.0120311	-3.48	0.001	.9339644	.9811393
lowcostdwelling_stone	1.068098	.0184001	3.82	0.000	1.03263	1.104785
highskills_complit	1.033075	.0127947	2.63	0.009	1.008295	1.058464
economically_inactive	.8976974	.0212164	-4.57	0.000	.8570546	.9402676
unemployed_strictlydef	1.124339	.0348659	3.78	0.000	1.058026	1.194809
chronicdisease_heart	.9747318	.0102015	-2.45	0.014	.9549372	.9949368
_cons	15.26496	.8297237	50.14	0.000	13.72207	16.98133

Source: Own calculations using NIDS dataset.

In estimating the comprehensive digital index, a statistically significant multiple linear regression model with an F Statistic [36, 6149] of 24.80 and a model p-value of 0.0000 explained 21.54 % of the variation in the response variable. The influence of the population grouping variable although statistically significant was less than 1 for each 1-unit change in the explanatory variable, that is, moving from African to Coloured, Indian or White population grouping increased the comprehensive digital index by less than 1. A large coefficient on the model's constant [15.26] is noticeable in the results in Table 31. Comparing these results with results in Table 12 for Wave 1 shows that the influence of the population grouping was also below 1 showing a very small influence of racial grouping. The model's constant [30. 36] was twice the value in Wave 5, and the explanatory power slightly smaller than the estimate in Wave 5. Ab observed in previous models, the comprehensive digital index was characterized by a large loading for access to digital smartphones and the models showed that the influence of socioeconomic characteristics, skills or social exclusion/inclusion were small based on the models' explanatory contribution based on these explanatory variables. Thus, the model continues to reinforce the understanding that the influence of socioeconomic characteristics, social inclusion/exclusion and skills on the comprehensive digital index is small based on the consistently small r-squared value. Access to digital smartphones and mobile devices has characterized various research papers which have reported a positive impact of these technologies on socioeconomic variables and social inclusion in the form of labour market participation (Conradie D.P., Morris C., and Jacobs S.J., 2003; Diga, Nwaiwu and Plantinga, 2013; Mishra, 2017). This study aligns with an empirical study that estimates that the impact is smaller than found in other studies (Bornman, 2016).

Table 32 shows results for the multiple linear regression modelling of the communication asset index using wave 5 of the NIDS data. The model with an F Statistic [38, 6147] of 22.39 and a model p-value of 0.0000 was statistically significant and explained 54.56 of the variation in the response variable based on the explanatory variables. Comparing the results of this model with those for Wave 1, it can be noticed that the large influence of the population variable on access to advanced digital technologies as measured by the communication asset index is non-existent, showing that the racial factor is no longer a significant influence on access to these technologies in South Africa. The influence of socioeconomic characteristics (household status -- well_to_do [1.64], employed status [1.44], income –aboveavg_income [1.05], household wealth – wealthy_class [1.12], household assets [1.06]) social exclusion (capmkt_access

[1.12], religious affiliation—noreligion [1.12], other_religion [1.06], labour market access—broadly_unemployed [1.46) and skills (secondary education [1.13]).

Table 32: Modelling the Communication Asset Index Wave 5

Survey: Linear regression

Number of strata =	53	Number of obs =	6,237
Number of PSUs =	6,237	Population size =	18,600,516
		Design df =	6,184
		F(38, 6147) =	22.39
		Prob > F =	0.0000
		R-squared =	0.5456

comms_asset_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
secondaryedu_skills	1.12639	.0583741	2.30	0.022	1.017577	1.246838
primaryedu_skills	.5949948	.0964585	-3.20	0.001	.4330045	.817587
matric_retail	.8522005	.0595492	-2.29	0.022	.743106	.977311
manufacturing_skills	.8351769	.0538623	-2.79	0.005	.7359901	.9477306
transcomm_skills	1.122526	.0384401	3.38	0.001	1.049644	1.200469
construction_skills	.9392414	.0156165	-3.77	0.000	.9091213	.9703595
transcomm_skills	1	(omitted)				
plantmachskills	.9527194	.0214177	-2.15	0.031	.9116449	.9956444
well_to_do	1.642985	.0345782	23.59	0.000	1.576579	1.712188
govt_grants	.9463118	.0142863	-3.66	0.000	.918716	.9747365
middle_inc	.9137888	.0168559	-4.89	0.000	.8813356	.947437
capmkt_access	1.122311	.0242951	5.33	0.000	1.075681	1.170963
employed_educ	1.436188	.1183315	4.39	0.000	1.221982	1.687943
lowlevels_edu	.5853957	.0964978	-3.25	0.001	.4237486	.8087063
indifferent	1.057652	.0214078	2.77	0.006	1.016507	1.100462
public_infrast	.9328983	.013338	-4.86	0.000	.9071142	.9594152
noreligion	1.120178	.0247057	5.15	0.000	1.072778	1.169672
aboveavg_income	1.057676	.0276121	2.15	0.032	1.004908	1.113214
modpref_leave	1.07374	.0200555	3.81	0.000	1.035135	1.113784
wealthy_class	1.117664	.0213974	5.81	0.000	1.076495	1.160407
other_religion	1.066278	.0257958	2.65	0.008	1.016889	1.118065
jewish	.9346712	.0219585	-2.88	0.004	.892601	.9787241
hsehld_assets	1.060592	.02281	2.74	0.006	1.016806	1.106264
employed	1.152851	.0502396	3.26	0.001	1.058454	1.255668
lowcostdwelling_rural	1.048352	.0203826	2.43	0.015	1.009146	1.08908
transportcomms_matric	1.175654	.108402	1.76	0.079	.9812471	1.408576
broadly_unemployed	1.462018	.1211146	4.58	0.000	1.242867	1.719811
lowcostdwelling_brickthatch	1.104588	.0299949	3.66	0.000	1.047326	1.164982
transportcomms_matric	1.175654	.108402	1.76	0.079	.9812471	1.408576
broadly_unemployed	1.462018	.1211146	4.58	0.000	1.242867	1.719811
lowcostdwelling_brickthatch	1.104588	.0299949	3.66	0.000	1.047326	1.164982
lowcostdwelling_timber	.9351402	.0227819	-2.75	0.006	.8915295	.9808843
manufacturingworking	1.213595	.1031477	2.28	0.023	1.027337	1.433621
transportcomms_work	.8252839	.043935	-3.61	0.000	.7434979	.9160666
lowskills_commskills	.8881936	.0325128	-3.24	0.001	.8266903	.9542725
commskills_mod	.9245319	.0209922	-3.46	0.001	.8842824	.9666135
commskills_poor	.9446633	.0191932	-2.80	0.005	.9077774	.9830481
commskills_vpoor	.9186824	.0183982	-4.24	0.000	.8833144	.9554666
highskills_complit	.8803897	.0245813	-4.56	0.000	.8334969	.9299206
economically_inactive	1.117821	.0484466	2.57	0.010	1.026771	1.216944
cleanenergy_solar	.981863	.004785	-3.76	0.000	.9725274	.9912883
cleanenergy_gas	.97696	.0110033	-2.07	0.039	.9556261	.9987702
_cons	.8410052	.045198	-3.22	0.001	.7569092	.9344447

Source: Own calculations using NIDS dataset.

The range of influential skills and competencies has significantly diminished when compared to Table 13 for the same analysis for Wave 1, while the range of socioeconomic characteristics has increased in Wave 5. The analysis shows that access to advanced digital technologies has expanded across population groups with the racial influence eliminated.

The results of the analysis of the computing skills index are given in Table 34, which reports the output of the multiple linear regression analysis which was statistically significant with an F Statistic [57, 6128] of 75.60 and a model p-value of 0.0000 and explained 76.03 % of the variation in the computing skills index based on the explanatory variables. The differences in computing skills accumulation based on population grouping are absent in the results of the analysis in Wave 5. In Wave 1, it can be noticed from Table 14 that being White increased the computing skills index by a coefficient of 1.88 when compared to being African. In Table 14. Skills were more important in explaining computing skills among individuals which when contrasted with results of the descriptive analysis shows that Whites and Indians were largely represented in high skilled occupations when compared with Africans. The results of the analysis of Wave 5, continues to show the influence of skills and socioeconomic characteristics on the computing skills index. A multivariate analysis of variance on the communication asset index and the computing asset index based on the population grouping variable shows that there were differences among the groups are presented in Table 33. The small p-values less than 5 % shows that the null hypothesis of no differences in effect among groups can be rejected. These results show that the differences observed in the descriptive analysis for Wave 5 of the NIDS data continue to hold for the skills distribution among population groups with Africans being concentrated in the low skills categories when compared to other population groups.

Table 33: Multivariate Analysis of Variance, assessing group differences on the Communication Asset Index and the Computing Asset Index.

```
. manova (comms_asset_index comp_lita_index) = population_grp

                      Number of obs =      47,033

                      W = Wilks' lambda       L = Lawley-Hotelling trace
                      P = Pillai's trace      R = Roy's largest root

              Source │ Statistic        df    F(df1,      df2) =    F   Prob>F
          ───────────┼──────────────────────────────────────────────────────────
          populatio~p│W    0.8938        3       6.0  94056.0    905.06 0.0000 e
                     │P    0.1062                6.0  94058.0    879.41 0.0000 a
                     │L    0.1187                6.0  94054.0    930.74 0.0000 a
                     │R    0.1183                3.0  47029.0   1854.41 0.0000 u
          ───────────┼──────────────────────────────────────────────────────────
            Residual │               47029
          ───────────┼──────────────────────────────────────────────────────────
               Total │               47032
          ───────────┴──────────────────────────────────────────────────────────
                      e = exact, a = approximate, u = upper bound on F
```

Source: Own calculations using NIDS dataset.

Table 34: Modelling the Computing Skills Index Wave 5

Survey: Linear regression

Number of strata =	53	Number of obs =	6,237
Number of PSUs =	6,237	Population size =	18,600,516
		Design df =	6,184
		F(57, 6128) =	75.60
		Prob > F =	0.0000
		R-squared =	0.7603

comp_lita_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
2.spatial	.8719786	.0413167	-2.89	0.004	.7946314	.9568545
2.gender_var	.8735616	.036559	-3.23	0.001	.8047544	.9482519
social_skills	1.574714	.1087576	6.57	0.000	1.375314	1.803024
financial_skills	1.390054	.0713737	6.41	0.000	1.256948	1.537255
construction_skills	.6838552	.0300592	-8.65	0.000	.6273961	.745395
well_to_do	1.069592	.011751	6.12	0.000	1.046802	1.092878
manufacturing_skills	.2691172	.0271686	-13.00	0.000	.2207965	.3280129
educ_access	1.231506	.0295137	8.69	0.000	1.174987	1.290744
below_average_inc	.9559737	.011209	-3.84	0.000	.9342508	.9782016
secondaryedu_skills	2.503582	.2391317	9.61	0.000	2.076073	3.019124
matric_retail	.2581828	.0359666	-9.72	0.000	.1964835	.3392568
lowskilled_mining	1.146746	.027799	5.65	0.000	1.093525	1.202557
miningskills_gen	1.512294	.0493322	12.68	0.000	1.418613	1.612161
energy_skills	.7732049	.0407411	-4.88	0.000	.6973245	.8573423
transcomm_skills	1.081714	.0164144	5.18	0.000	1.05001	1.114375
clericaladmin_skills	13.38731	1.992506	17.43	0.000	9.999534	17.92285
plantmachskills	1.035525	.0117514	3.08	0.002	1.012743	1.05882
servicewrk_skills	1.046827	.0105141	4.56	0.000	1.026417	1.067642
elementary_skills	.9671072	.0084068	-3.85	0.000	.9507666	.9837287
crafts_trades_skills	.9635114	.0107936	-3.32	0.001	.9425828	.9849046
security_skills	127.4493	70.82317	8.72	0.000	42.87803	378.8262
skilled_agricwrk	74.6756	53.0472	6.07	0.000	18.55212	300.5826
technicalskills	1.222081	.049483	4.95	0.000	1.128827	1.323038
labmkt_active1	.7202524	.0264461	-8.94	0.000	.6702306	.7740074
capmkt_access	1.036959	.0122388	3.07	0.002	1.013242	1.061231
sedentary2	.9427563	.0146345	-3.80	0.000	.9144997	.971886
indifferent	.9679715	.0138205	-2.28	0.023	.9412542	.9954472
verylow_income	.9598166	.0131618	-2.99	0.003	.9343585	.9859683
noreligion	.9590558	.0102156	-3.92	0.000	.9392373	.9792925
modpref_leave	.9502496	.0106529	-4.55	0.000	.9295941	.9713641
strongprof_leave	.9707121	.0125737	-2.29	0.022	.9463735	.9956766
wealthy_class	.9608265	.0151397	-2.54	0.011	.9316012	.9909687
unemployed_disc	.811255	.0209647	-8.09	0.000	.7711806	.8534119
publicwater_inf	.9468356	.0105789	-4.89	0.000	.9263227	.9678028
hsehld_assets	1.047821	.0136506	3.59	0.000	1.0214	1.074925
piped_wateraccess	1.058894	.0164554	3.68	0.000	1.027122	1.091648
medsized_hsehld	1.04121	.0168128	2.50	0.012	1.008767	1.074696
employed	1.335814	.0518134	7.46	0.000	1.238007	1.441347
secondary_edu	.4995018	.0412665	-8.40	0.000	.4248161	.5873178
publicwater_inf3	.9709685	.0092543	-3.09	0.002	.9529954	.9892807
transportcomms_matric	2.716775	.339212	8.00	0.000	2.12693	3.470196
professional_socialservices	.592153	.0581819	-5.33	0.000	.4884081	.7179348
broadly_unemployed	1.120555	.0219552	5.81	0.000	1.078331	1.164432
lowpaid_miningwork	1.211297	.0362681	6.40	0.000	1.142245	1.284523
vocational_financialservices	.7711139	.0503863	-3.98	0.000	.6784038	.8764937
largehousehold_extra	1.03857	.016336	2.41	0.016	1.007035	1.071093
lowcostdwelling_stone	1.294874	.0440762	7.59	0.000	1.211289	1.384227
manufacturingworking	1.929953	.1294463	9.80	0.000	1.692169	2.201152
constructionworking	.7125132	.0318821	-7.58	0.000	.6526758	.7778364
technical_working	.8568706	.0344772	-3.84	0.000	.7918801	.927195
energy_working	.8465422	.0347165	-4.06	0.000	.7811496	.9174091
commskills_mod	1.077718	.0136845	5.89	0.000	1.051222	1.104881
commskills_poor	1.049464	.010752	4.71	0.000	1.028596	1.070754
commskills_vpoor	1.030988	.0099576	3.16	0.002	1.011651	1.050694
highskills_complit	2.147564	.0599029	27.40	0.000	2.033286	2.268264
medskills	6.29681	.758679	15.27	0.000	4.97213	7.974414
lowcostenergy_kerosene	1.013302	.0058818	2.28	0.023	1.001837	1.024898
_cons	1.37415	.0717602	6.09	0.000	1.240436	1.522277

Source: Own calculations using NIDS dataset.

Table 35: Modelling the Basic Computing Index Wave 5.

Survey: Linear regression

Number of strata = 53	Number of obs = 6,237
Number of PSUs = 6,237	Population size = 18,600,516
	Design df = 6,184
	F(43, 6142) = 169.02
	Prob > F = 0.0000
	R-squared = 0.7452

comp_litb_index	exp(coeff.)	Linearized std. err.	t	P>|t|	[95% conf.	interval]
population_grp						
2	1.450287	.1095945	4.92	0.000	1.2506	1.681859
3	4.217647	.8008857	7.58	0.000	2.906729	6.119781
4	1.977864	.2522778	5.35	0.000	1.540295	2.539738
social_skills	1.243395	.0353205	7.67	0.000	1.176047	1.3146
financial_skills	1.297329	.0405553	8.33	0.000	1.220213	1.379318
transcomm_skills	1.057922	.0090355	6.59	0.000	1.040357	1.075784
labmkt_active1	.7664409	.0200841	-10.15	0.000	.7280631	.8068416
vocational_financialservices	.6915685	.0279604	-9.12	0.000	.6388724	.7486112
lowskills_commskills	3.138237	.0664542	54.01	0.000	3.010631	3.271252
medskills	1.214845	.0223171	10.59	0.000	1.171874	1.259392
economically_inactive	.7896722	.0305165	-6.11	0.000	.732059	.8518194
manufacturing_skills	.9711503	.0134543	-2.11	0.035	.9451301	.9978868
hsehldwrk_skills	.9643156	.0127497	-2.75	0.006	.939643	.9896362
clericaladmin_skills	.6802526	.0407212	-6.44	0.000	.6049307	.764953
plantmachskills	1.071976	.0158221	4.71	0.000	1.041404	1.103446
servicewrk_skills	1.077391	.0083867	9.58	0.000	1.061075	1.093958
elementary_skills	1.049444	.016961	2.99	0.003	1.016716	1.083226
crafts_trades_skills	1.090277	.0180996	5.21	0.000	1.055366	1.126342
security_skills	51.51525	16.62111	12.22	0.000	27.36822	96.96723
skilled_agricwrk	378.4604	171.0626	13.13	0.000	156.029	917.9849
technicalskills	1.018418	.0052708	3.53	0.000	1.008138	1.028803
sedentary	.6099687	.0185505	-16.25	0.000	.5746662	.64744
educ_access	1.07157	.0210482	3.52	0.000	1.031093	1.113637
sedentary2	.8410497	.010985	-13.25	0.000	.8197886	.8628622
employed_educ	.8635251	.0328074	-3.86	0.000	.8015479	.9302945
lowlevels_edu	1.225507	.0364097	6.84	0.000	1.15617	1.299002
below_average_inc	.8679176	.0096964	-12.68	0.000	.849116	.8871355
indifferent	.8691045	.011326	-10.77	0.000	.8471828	.8915934
verylow_income	.901023	.0086479	-10.86	0.000	.8842285	.9181364
noreligion	.8852641	.0086816	-12.43	0.000	.8684077	.9024478
modpref_leave	.9094828	.0085932	-10.04	0.000	.8927921	.9264854
strongprof_leave	.9137637	.0101284	-8.14	0.000	.8941227	.9338361
wealthy_class	.9357162	.0085452	-7.28	0.000	.9191138	.9526186
employed	.7460558	.038568	-5.67	0.000	.674154	.8256262
certified_socialservices	.7830264	.027203	-7.04	0.000	.7314744	.8382117
sanitation_pitlatrine	1.021283	.0093316	2.30	0.021	1.003153	1.039741
no_schooling	1.244601	.0463644	5.87	0.000	1.15695	1.338892
broadly_unemployed	1.198767	.0618606	3.51	0.000	1.083431	1.326381
commskills_mod	1.830502	.0247097	44.79	0.000	1.782698	1.879588
commskills_poor	1.49264	.0183501	32.58	0.000	1.457097	1.52905
commskills_vpoor	1.535336	.0182616	36.05	0.000	1.499951	1.571556
independently_employed	1.036206	.0134593	2.74	0.006	1.010155	1.06293
unemployed_strictlydef	1.211305	.0634084	3.66	0.000	1.093168	1.34221
_cons	.961768	.0243896	-1.54	0.124	.9151249	1.010789

Source: Own calculations using NIDS dataset.

In Table 35, the multiple linear regression model of the basic computing skills index is presented. The MLR model with an F Statistic [43, 6142] of 169.02 and a model p-value of 0.0000 was statistically significant and explained 74.52 % of the variation in the response variable based on the predicting variables in the model. The influence of the population grouping on the basic computing index is still noticeable in the results. Compared with being in the African population group, being Coloured increases the basic computing skills index by 1.45, being Indian by 4.21 and being White by 1.98. The influence of skills categories can be seen in the table with social skills, financial skills, transport and communication sector skills, communication skills, middle job skills and other skills have strong coefficients and are positively associated with the basic computing skills index. In Wave 1, there was no decomposition of advanced computing skills and basic computing skills, although the influence of the population grouping variable can be observed in Table 14. In Table 35, the large coefficients on security skills [51.51] and skilled agriculture [378.46] are significant.

Finally, a multivariate analysis of variance of the communication asset index, the advanced computing skills index and the basic computing skills index over population and gender showed statistically significant differences. The results of the omnibus multivariate analysis of variance analysis are presented in Table 36 below. The multivariate analysis of variance showed a very small p-value demonstrating that the null hypothesis of no differences in the group mean values can be rejected. The distribution of the communication asset index, the advanced computing skills index and the basic computing skills index are observed to have a distinct population and gender group profile. These population and group differentials were observed in Wave 1 and are demonstrated to continue to exist in Wave 5. These differences were observed in the descriptive analysis which assessed the mean of these indices across population group, gender and other demographic variables. These differences are explained by socioeconomic characteristics, social inclusion/exclusion and skills profile of individuals across South Africa as the results are nationally representative based on the design of the NIDS survey (Leibbrandt and Woolard, 2016; Brophy *et al.*, 2018).

Socioeconomic characteristics included the household income, occupational status, household assets and access to household level infrastructure. Social exclusion included variables measuring labour market participation, access to education and training institutions, religious affiliation, access to developmental opportunities, public services and access to infrastructure and services. Finally, skills included financial skills, professional careers, communication skills, transport and logistics skills, middle job skills and computer skills. A study found access and opportunity and factors deepening the digital divide in South Africa (Brown and Czerniewicz, 2010). A study on digital inequalities and their effects on social inequalities found that the observed pattern of internet access among university students masked household-level socioeconomic inequalities which digital inequalities exacerbates the observed existing social inequalities (Oyedemi, 2012). Another study confirms the existence of gender gaps, differences in educational levels among population groups and affected internet usage and computer use and without addressing these dynamics, bridging the digital divide and enabling transition into the information society will be a challenge for South Africa (Bornman, 2016).

Table 36: The multivariate analysis of variance of the communication asset index, the advanced computing skills index and the basic computing index over population and gender groups.

```
. manova (comms_asset_index comp_lita_index comp_litb_index) = population_grp gender_var

                 Number of obs =     46,959

                 W = Wilks' lambda      L = Lawley-Hotelling trace
                 P = Pillai's trace     R = Roy's largest root
```

Source		Statistic	df	F(df1,	df2) =	F	Prob>F	
Model	W	0.8919	4	12.0	124223.6	457.64	0.0000	a
	P	0.1084		12.0	140862.0	439.98	0.0000	a
	L	0.1210		12.0	140852.0	473.38	0.0000	a
	R	0.1188		4.0	46954.0	1393.95	0.0000	u
Residual			46954					
populatio~p	W	0.8924	3	9.0	114269.0	608.14	0.0000	a
	P	0.1078		9.0	140862.0	583.49	0.0000	a
	L	0.1204		9.0	140852.0	627.97	0.0000	a
	R	0.1185		3.0	46954.0	1854.51	0.0000	u
gender_var	W	0.9995	1	3.0	46952.0	7.39	0.0001	e
	P	0.0005		3.0	46952.0	7.39	0.0001	e
	L	0.0005		3.0	46952.0	7.39	0.0001	e
	R	0.0005		3.0	46952.0	7.39	0.0001	e
Residual			46954					
Total			46958					

e = exact, a = approximate, u = upper bound on F

Source: Own calculations using NIDS dataset.

5.11. Chapter summary

In the quantitative analysis presented in this chapter, the attempt was made to portray the influence of socioeconomic conditions in accessing digital technologies and developing the skills necessary to adapt to a digitally transforming environment. The descriptive analysis showed clearly that the socioeconomic divide had a strong population grouping dynamic, with the African population grouping exhibiting very limited and disadvantaging socioeconomic performance across the period in which the surveys of the national income dynamics study were conducted. The multiple linear regression models using survey design showed robust findings and demonstrated the differences in the socioeconomic variables that were associated with each subgroup of the digital index. However, with the population grouping variable in the modelling as an explanatory variable, the same characteristics in the socioeconomic divide were apparent. The results showed that the socioeconomic divide influences access to digital technologies, digital skills and material welfare, and will determine largely the adaptive capacity of individuals and households in the face of pervasive change.

CHAPTER 6: PRESENTATION AND INTERPRETATION OF QUALITATIVE ANALYSIS FINDINGS.

6.1. Introduction

This chapter is a presentation of the results of the thematic analysis method used in the analysis of the digital transformation qualitative data to provide answers to the questions of the research study. In the discussion, the substantive concepts from the analysis are presented with references to the extracts from which such concepts were derived referenced as (P#). Four major themes are presented which are conceptualisation and processes of digital transformation, opportunities and challenges of digital transformation, DT and socioeconomic outcomes and finally, the mitigation of adverse outcomes of digital transformation.

6.2. Conceptualisation and Characteristics of DT

6.2.1.1. DT as an Open Ecosystem

As a broad ecosystem for social and economic governance, DT is understood to comprise networking infrastructure, collaboration capabilities, security technology, mobility infrastructure and education reform systems to create the workforce to participate in the DT ecosystem (P1). It is an interoperable open ecosystem of technology with global democratisation of capabilities, layered broadband capabilities, platforms, sensors with billions of connected devices creating a massive network effect (P8, P19). This places DT within the premise of a general-purpose technology platform, creating new arrangements for economic and social activity, with specific requirements (network infrastructure) and skillsets (capabilities and competencies) hence the need for complementary institutions (educational systems). This ecosystem makes innovation possible for customers in the forms of new products and the creation of new businesses generating needed economic growth and other social positive outcomes (P19). Digital skills and capabilities are central to participation in this developing platform for economic reproduction, such as the technology, internet connectivity, access to devices and network societies for collaboration. The inclusion of mobility infrastructure induces flexibility and speed that differentiates this ecosystem from previous arrangements of economic reproduction and exchange, such that transactional interaction ceases to be confined to static spaces. Data flowing through massively connected devices and projected to grow exponentially generates a connected global ecosystem with important network effects.

"Well, I'm thinking about the cord networking infrastructure that runs the underlying internet clearly, yeah. But collaboration capabilities, the security technology, the mobility infrastructure that goes into service provider networks all of that is part of this broad ecosystem that delivers it every day. And then we even subsequently created a global educational network called Network Academics to create more people who can be part of this ecosystem" (P1[2]).

And then the third is how they use this digital world as a source of innovation for their customers, how they design new products, new services and in some cases whole new businesses that they can generate to drive growth in a world where growth is increasingly hard to find" (P19[3]).

I think the power of what has been created with the internet is it's ever someone owns every piece of equipment that connects right, someone has title to it. This interoperable sort of open ecosystem of technology has created a democratisation of capabilities around the world. You layer onto it broadband and the capabilities, and I think you do have the opportunity. So, I think it'll continue to we're going to go from 18 billion connected devices to 50 billion in 2020 and perhaps 500 billion in 2030, so that's a massive network effect" (P1).

"And needless to say, when we went into digitization, we knew connectivity, we knew the software, but when you go into the cloud, you can't do everything alone. And the big thing for me is that this world is prone to a lot of partnerships. So, the big bet you have to do is choose the right partners and your success is dependent on you but also on the ecosystem you are choosing" (P8[4]).

Positioning these findings in light of the quantitative analysis in Chapter 5 shows that the lack of digital capabilities and competencies among a greater proportion of the population will limit the effect of these positive effects of digital transformation. As observed in the quantitative analysis while among many South African, digital integration has been through mobile platforms and connectively however these have not translated to advanced ICT skills which continue to have a racialized profile and which are key to beneficial participation in digital transformation. The continued digital divide in skills will likely exacerbate the challenges of social inequality, socioeconomic outcomes and structural unemployment as digital

[2] Chuck Robbins, CEO, Cisco, USA at Davos 2016: A new platform for the digital economy, www.weforum.org/
[3] Rich Lesser, Global Chief Executive Officer and President, Boston Consulting Group, USA. Davos 2016, The digital transformation of industries @ WEF, https://youtu.be/qav1y7G15JQ?t=3
[4] Jean Pascal Tricoire, Chairman and Chief Executive Officer, Schneider Electric, France. Davos 2016, The digital transformation of industries, www.weforum.org/

transformation as conceptualized advances as many will be marginalized. A study identified the attributes of digital transformation as conceptualised pointing out disruptive technologies directed at productivity improvements, value creation and social welfare. The study also aligns with the finding that there is a limitation conceptualisation of the positive effects of digital transformation based on individual characteristics, shortage of skills and a qualified labour force, lack of sufficient infrastructure and poor policy environments (Ebert and Duarte, 2018).

6.2.1.2. DT as tech-based Business model transformation

The dominant conceptualisation of DT among the participants was the idea of DT as an accelerated technology-based business transformation, with migration from non-digital and analogue systems to internet-based platforms. DT is a business model transformation built around digital technological innovation in technologies such as 3D printing, sensor technology and generating new applications, not before possible (P4). DT is thought of as a transformation of the production and exchange arrangements of a society caused by changes in the general-purpose technology platform (P4). This is understood to be propelled by convergence in technological innovations such as information technology, biotechnology, manufacturing technology to bring about business/industrial model transformation (P4). Technology is the core of business model design, connecting companies, industries and consumers with a shared understanding of the platform and technology in business value chains (P2, P3, P1). Individuals and organisations leverage technologies of diverse technology providers to create a platform economy around the industry, creating business to business collaborative environments (P3).

Based on this understanding, DT is driven by productivity and efficiency considerations in business model design, with technologies offering a pathway to achieve productivity and efficiency, and business expansion while reducing business costs, presenting a business case for digital transformation. Innovative technologies will drive differentiated business models and differentiated business strategies for the future. The resulting economy is based on platforms acting as mediums of exchange of economic information and decisions driven by the exchange of consumer and industry data. This transformation is global with relevancy and competitive capacity determined by how companies reinvent themselves in line with the changed technological arrangements which will transform the way businesses operate (P4, P3). Access to technology, infrastructure, skills and finance towards the development of competencies are key determinants of participation in the new economy within this strand of thinking. However, the pervasive transformation of technology across businesses in the economy, implies that technology will likely power even businesses within the non-technology sector thus raising total factor productivity with positive returns to the economy and society.

"Of their current business on how you emulate this platform concept. Yes, how you leverage the technology of the different technology providers to create a platform economy more around the industry so here we talked about a lot around platforms that could be used by consumers to platforms which are more in the business-to-business environment" (P2[5]).

"The strategy of every business is going to have technology at the core right. We've gone through this phase where every customer, every company, every country knows that technology has to enable your strategy ... that technology will fundamentally define, differentiated business models and differentiated business strategies" (P1)

"I mean the three are platforms within a company. Yes, platforms within an industry and platforms we are going to create across industries, so you see now a very clear typology of this different platform enabled by the internet of things and digital technologies, and we are going to change, dramatically the way the businesses operate" (P3[6])

"It's Darwinism, and so we all have a responsibility to continue to make our companies relevant and reinvent because you know listen the whole world has changed and if you do not reinvent, you'll be eclipsed and it's a challenge for the big companies and the older companies" (P4[7]).

6.2.1.3. DT as the Fourth Industrial Revolution

DT as the fourth industrial revolution contrasts it with previous periods of technological innovation. This conceptualisation raises issues of job creation, socioeconomic inclusion and skilling the workforce to meet the challenges of the digital economy (P6). This industrial revolution involves a rewiring of business with the use of advanced digital technologies, leveraging massive amounts of data, advanced analytics and cloud computing creating a source of innovation for customers (P7, P8). Digitization consisting of customer relationship connectivity, the internet of things, collaboration and open information access are elements of this fourth industrial revolution, giving economic and social agents, a better understanding of

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[5] Pierre Nanterme, Chairman and Chief Executive Officer, Accenture, France, at Davos 2016, A new platform for the digital economy, www.weforum.org/

[6] Klaus Kleinfeld, Chairman and Chief Executive Officer, Alcoa, USA: Davos 2016, The digital transformation of industries, www.weforum.org/

[7] Meg Whitman, President and Chief Executive Officer, Hewlett Packard Enterprise, USA: Davos 2016, the digital transformation of industries, www.weforum.org/

the world, better shaping of outcomes in the design of interventions, determining and predicting the future stakeholders would like to materialise and allocate resources towards achieving that future (P8, P9). Finally, understanding DT as the fourth industrial revolution stresses the point that the world is in a technological revolution radically different from previous revolutions and build on different technological apparatus, such that the technology shifts and changes are going to be realized at a scale never before experienced (P10).

"So, we are here to talk about … how to create jobs and inclusion and a workforce that is ready to grapple with the fourth industrial revolution. What is the role of business, what is the role of the public sector?" (P6[8]).

"… digitization, customer relationship connectivity of products supply chain the way we work together with the need to integrate them, it's rotating fast and you need to connect everything with the rest so just like a need for consistency which is—I don't know if we call it the fourth and things but being sharp on where you want to make a difference, and be very sharp on the partners you want to associate with" (P8).

"It is the connectivity of devices and sensors that ultimately in a fabric of software analytics and technology give us the ability to understand our world, better shape outcomes, determine and predict what it is we'd like to have happened and drive resources towards them" (P9[9]).

"We are in a technology revolution; we are going to see technology shifts and changes at a scale that we have never seen on this planet. We've been talking about the fourth industrial revolution, and how that is not just about digital technology, that's about many different types of technology including bioengineering technology and advancements in genetic engineering, ... These are things that the world has never seen, but this amount of transformation underway requires severe and extreme leadership and that is what we need, we need stronger leaders who can give us a stronger vision for where we are going" (P10[10]).

6.2.1.4. Characteristics of digital transformation

DT was described to be characterised by the speed of technological innovation and wide adoption in business and society both locally and globally (P12, P13). There are accelerated

[8] Rana Foroohar, Global Business Columnist and Associate Editor, Financial Times, Davos 2019, A jobs strategy for the Fourth Industrial revolution, https://www.weforum.org/events/world-economic-forum-annual-meeting-2019/sessions/a-jobs-creation-strategy-for-the-fourth-industrial-revolution

[9] Robert F Smith, Chairman and Chief Executive Officer, Vista Equity Partners, USA. Davos 2016, The internet of things is here, www.weforum.org/

[10] Marc R Benioff, Chairman and Chief Executive Officer, Salesforce, USA. Davos 2017, The future of growth, technology driven, human centred, https://youtu.be/QCvtv5VMskI?t=8

changes in the management of production and service provision (P13). The size and speed of change remain an unknown variable, creating uncertainty and risk, particularly in the design of interventions for those who are net consumers of technology, not frontlines of digital technology development (P15). Therefore, while technologies have been developed, adopted and integrated with the previous revolutions, the pace at which technologies are developed and integrated in this era presents a stark contrast, requiring novel forms of organisation for fast-paced change. The characteristic speed associated with DT stems from technologies that transform traditional conceptions and practices of business. Platforms, applications and devices accelerate change through accelerating communication technology thus enabling speedier execution (P16). Through these dramatic changes, social and economic challenges are inevitable as economic agents have to adjust as rapidly as technology advances to remain employable and productive in a dynamically changing environment. The need for speed can create paranoia and unhealthy competition, because of the perception that some other organisation is moving faster than our own, with organisations that can invest and innovate faster benefiting more from increased income through digital transformation. Unhealthy competition can result in misallocation of resources and poor systems for the redistribution of gains possible through digital transformation. Accelerating business transformation will require increased governance with downsizing will likely be of common occurrence, with adverse effects of employment due to technology displacement (P18). The speed attribute of DT eliminates lags between technology development and adoption into businesses, markets, industries and societies. Thus, societies experience changes whether they can adjust and adapt or not with those who can access, adapt and integrate the technologies faster benefiting from the DT divided. Applications can automate work and with their evolution encompass more of human work and enable accelerated technology development due to data inflows. Thus, with each wave of technological advance or upgrading, human instrumentality in mediating work will likely experience a heightened risk of displacement and job destruction.

"So, it is a matter of the use of the technology and then how you integrate it. But for trade unions, we have been integrating technology for decades. You are right that what's different now is the speed and the dramatic shifts in the way production is managed or the way we're dealing with services of any kind" (P12[11]).

[11] Sharan Burrow, General Secretary, International Trade Union Confederation (ITUC), Belgium. Davos 2019, A jobs strategy for the fourth industrial revolution, https://youtu.be/tvnyWYHrIdY?t=4.

"Yeah, thanks to creativity, new industries, new jobs will be created. The big challenge for me from what we see at 100,000 customers we have in 60 countries is the speed of the transition because technology is making its inroads extremely fast and the question to challenge how does society, companies and employees adapt to this acceleration of technology inroads. So, the key challenge is about the speed and the way we transition from one system to the new—to the future of work" (P13[12]).

"First, we share with you all the fact that the size and speed of change is unknown. So, we face together an unknown. So, we have to organise in a different way to face the unknown. We estimate 10-15 per cent of the job will be suppressed in the coming 10 years" (P15[13])

"Of course, first of all, we need to understand this fourth industrial revolution and technology is coming should be the technologies that actually can make this planet sustainable, because many of the previous industrial revolutions have used a lot more natural resources and if we want to have equality and everyone have the same possibilities, we need technologies that are coming out on global platforms and things like that" (P16[14]).

"Importance of speed, I mean not that it wasn't on my radar but as we are now, we've decided to separate the company so that both entities have their unique profile and the speed with which we have to do this and we have to continue to—speed is everything" (P18[15]).

6.3. Opportunities of Digital Transformation

DT and its technologies are perceived as net employment generators though initially there are periods of disruption (P6). While previous periods of technological progress have created negative outcomes over the long-term through unsustainable resource use, DT will bring about planetary sustainability, through the promotion of sustainable resource usage enabled through advanced technology adoption (P16[16]). Technology augments human skills and consequently human productivity, by concentrating human resources in their most productive commitments since labour is freed from tasks and jobs that can be done more efficiently through technology (P13, P19). Releasing human labour from routine and automatable tasks results in technology

[12] Alain Dehaze, Chief Executive Officer, Adecco Group, Switzerland. Davos 2019, A jobs creation strategy for the Fourth Industrial Revolution, https://youtu.be/tvnyWYHrIdY?t=3
[13] Muriel Penicaud Minister Labour, France. Davos 2019, A jobs strategy for the fourth industrial revolution, https://youtu.be/tvnyWYHrIdY?t=3
[14] Hans Vestberg, Chief Executive Officer, Verizon Communications USA. Davos 2019, A jobs strategy for the fourth industrial revolution, https://youtu.be/tvnyWYHrIdY?t=4
[15] Klaus Kleinfeld, Chairman and Chief Executive Officer, Alcoa, USA, Davos 2016, The digital transformation of Industries, https://youtu.be/qav1y7G15JQ?t=1
[16] Hans Vestberg reference P16 "….technology is coming should be the technologies that actually…"

producing scope for better interpersonal relationships and higher-end development of human skills and competencies, thus making societies more productive. Digital technologies are a source of innovation generating new products, new businesses driving productivity growth and income (P19), broadening opportunities for investing in human development (P24). Smart technologies, smart contracts and direct access networks can be leveraged to the periphery and remote undeveloped locales (P24).

Technology increases productivity in sectors that were not traditionally technology-driven raising factor productivity. Thus, when general-purpose technologies are adopted, the whole society, even those sectors not directly connected with technology, becomes more productive (P25). Access to digital materials such as books and online learning platforms accessible through mobile applications can increase access to learning materials for low income-low skills groups, thus bringing skills to low income and under-skilled populations. Large inflows of data through AI applications in driving, assistive technology and medical diagnostics can be instrumental in aiding decision making through AI systems, better public governance, better health management and productivity. Technology provides the tools to solve societal problems on a large scale, enabling better regulation and governance (P26). Technology drives value creation creating jobs, training programmes and opportunities, and connectivity giving societies access to education in high-end skills, such as creativity, entrepreneurship, digital skills and critical thinking (P28, P27).

"... but if you look historically, technology has always been a net new jobs creator. However, there are periods of disruption" (P6)

"Thanks to technology, we can amplify the human resource, we can concentrate the human resource on what they like to do. So, we should look at the opportunities of the technology" (P13[17]).

"And then the third is how they use this digital world as a source of innovation for their customers, how they design new products, new services and in some cases whole new businesses that they can generate to drive growth in a world where growth is increasingly hard to find" (P19[18])

[17] Alain Dehaze.
[18] Rich Lesser.

"Not surplus in the old days where we thought you have to migrate and get labour population. To my mind, India is going to do just fine because we live in the villages and if we make our villages smart then frankly there is going to be huge productivity gains, in fact, an explosion of productivity" (P24[19]).

"Woman named Reeza in the Philippines she worked on an island she was commuting to school by boat a typhoon hit her island, the school was over for her, because of free basics, the program to provide free data to Facebook and other services we provide she connected to the internet finished her courses online now is gainfully employed. I think one thing that's often overlooked is that technology doesn't just create technology jobs, it powers jobs in the non-tech sector and that explains some of the promise of what you're talking about" (P25[20]).

"I think one point which we are all missing is technology can solve some of the problems at a very large scale I think that's something which we should not undermine, yeah and one brilliant example that I can give is the government of India implemented a unique identity for citizens for 1.2 billion people which is simple and secure and which is biometric, which is more advanced than any other ID system that's there in the developed world" (P26[21])

"The future will see AI systems acting in the same environment as humans in areas as diverse as driving, assistive technology and health care in medical diagnostic support systems…AI can make sense of the huge volume of data surrounding us, transforming data into knowledge that we can use to make better decisions in all these areas of personal and professional life…This could potentially lead to great transformations and to solving some of the most difficult problems in our society" (P27[22])

"So, we have to acknowledge that technology can be a force for value creation. Value creation creates jobs, it creates great training programmes, it creates opportunities, we have to put technology in the context of experiences" (P28[23]).

[19] Anand Mahindra, Chairman and Managing Director, Mahindra Mahindra, India. Davos 2016, The transformation of Tomorrow, https://youtu.be/mtXfzd53wRQ
[20] Sheryl Sandberg, Chief Operating Officer and Member of the Board, Facebook, USA. Davos 2016, The Transformation of Tomorrow, https://youtu.be/mtXfzd53wRQ
[21] C Vijayakumar, President and Chief Executive Officer, HCL technologies, USA. Davos 2019, Making digital globalisation inclusive, https://youtu.be/1helXRvkXNs
[22] Francesca Rossi, IBM Fellow and AI Ethics Global Leader, Thomas J Watson Research Centre, USA. Devoxx France, Artificial Intelligence Ethics, https://youtu.be/CsA_NhqMLCM
[23] Bill McDermott, Chief Executive Officer, SAP Germany. Davos 2019, Business Leadership in the Fourth Industrial Revolution, https://youtu.be/7uAmMdHCjSY

6.3.2. Challenges of Digital Transformation

6.3.2.1. Technology induced unemployment

Digital technologies will permeate societies and define every aspect of work, society and business strategies transforming the nature of work. Through the application of digital technology in routine and other forms of knowledge work, job displacement will likely be experienced in aspects of work not currently expected (P30). Digital embeddedness while transforming existing forms of work, creates digitally-enabled jobs, whose skillsets are presently in deficit creating skills crisis (P21), and net job loss (P20). In the developed world, middle-income, middle-skilled jobs have been on the decline while an increase in demand for highly skilled workers is noticeably on the rise (P33). Platforms have created forms of work with low income, unregulated and poor job security (P22). These job losses are a result of a qualitative change in the productive apparatus with traditional interventions such as strengthening the labour movement or raising the minimum wage becoming inefficacious in preserving employment in displaced work. Traditional entrepreneurial activity will not solve the displacement as it focuses on routine work which is better undertaken by machines and thus automated (P36). Loss of employment through job displacement implies that the initial stages of DT are associated with redistribution of income towards those developing and working with the emerging technology platform. The capital share of income will rise while productivity gains will not be reflected in expanding labour share of income, particularly the incomes of the average and median workers (P22). If technology displaces jobs and incomes of people, then new businesses might not flourish as predicted since there is less demand to sustain new business development, with possible worsening of human development indicators (P22). However, countries with high per capita capital have the lowest rates of unemployment, demonstrating that technology adoption on a massive scale is inversely associated with unemployment. These countries, however, are at the leading edge of technological advance and have the institutional capacity, making the migration of displaced workers in other sectors more manageable (P23). Thus, technology-induced unemployment will be greater where digital technology integration is within the context of a broadly under-skilled labour force.

"When I say there's a skills crisis, I do believe 100 per cent of jobs will change, and if you look, there's all different statistics, everyone in here has. I looked at the jobs created in the US in the recent 10 years, two-thirds are all digitally-enabled jobs" (P21).

"Yes, it is true that advance of technology has reached a point where intelligent systems can now for the first time do knowledge work in a way that we were never able to do before" (P30[24])

And those technologies are rapidly getting better at work that we used to think of as a little bit less routine, at recognising patterns, at understanding human speech and responding to it. Now my point is that those routine jobs, jobs doing that kind of routine work are not coming back" (P36[25])

"I would say there isn't going to be a sector of the economy that is somehow not racing with digitisation helping it drive productivity so there is not going to be a job that somehow you're dealing with the core aspects of digital technology, as in a farmer or as someone who is a former industrial company, any kind of job is going to have digital technology component that's going to be an increasingly significant part of it" (P20)

"There has been a declining middle class and middle-income jobs and mid-level jobs in the United States for 30 years, and it has been driven largely by technology … but the tasks that people do right now can be done right now, with the technology that we have right now" (P22).

"Strengthening the labour movement will not bring them back, raising the minimum wage will not bring them back. A bit more controversially, entrepreneurship will not bring them back, because the companies that entrepreneurs are starting up today are not employing people to do routine, knowledge processing work. That work is better off automated" (P36).

"One of the things we can see most clearly in the developed countries is that the productivity gains are not showing up in the incomes of the average or median workers. They're showing up in the profits, they're showing up in that very small sliver of the population whose talents are enhanced by the technology, not substituted for it by the technology. Well, if this is the case, this is a huge problem, because as technology takes out jobs, it takes out income. Where does the demand for future goods and services come from if the income of the consuming class is not growing commensurate with productivity, but is significantly slower than productivity?" (P22).

[24] Vishal Sikka, Chief Executive Officer and Managing Director, Infosys, USA. Davos 2016, Educating the Masters of the Fourth Industrial Revolution, https://youtu.be/anL2TdEl488

[25] Andrew McAfee, Principal Research Scientist, MIT Initiative on the Digital Economy, Massachussetts Institute of Technology, USA. Davos 2016, The promise of progress, https://youtu.be/ASsLyeZHP7Y

"I don't know if robots per capita are measurement but if it were, you know it seems to be the countries that are most robotized have the lowest unemployment rates. So, I am not convinced that technology is necessarily a big part of the problem" (P23).

6.3.2.2. Digital transformation, the digital divide and access imbalances

The digital divide is the source of negative outcomes of DT and is understood as digital inequality (P2, P38, P25, P21), net technology consumption (P39, P12, P40), technological inequality and the adoption curve (P29), digital literacy (P21, P26, P17, P42, P17), poor connectivity leading to poor access to data, digital skills and competences (P45).

6.3.2.2.1. Digital Inequality

Digital inequality refers to the proportion of people not having access to digital technologies and not being able to participate in the internet revolution. At the centre of the problem is the greater proportion of people in the emerging and developing economies experiencing connectivity issues (P2). These do not have access to this transformative technology and are attributable to financial challenges, lack of infrastructure and subsisting under conditions of economic vulnerability since the majority of people in the developing world live under conditions of poverty (P38). Stable income enables internet connectivity, and the vast majority live under the poverty line as set by the World Bank, and cannot afford extended online internet access or other online activities (P25). In bridging these inequalities and accumulating skills towards acquiring digital literacy, there is a need for continuous learning which requires financing particularly given the rate at which technology advance is making headways in the present era. Finally, even in the advanced world, because of the falling share of labour in income, the rate of saving per capita has declined with people living on the margins of financial vulnerability exacerbated by technology-induced job displacement (P38).

"The first inequality is the digital divide is the number of people not having access and not being able to participate in this internet revolution" (P2[26])

"there's the issue about digital inequality and the fact that not everyone has access to this amazing new transformative technology" (P38[27])

"So free basics is our program to bring connectivity to the people who don't have it, four billion people in the world can't access data and I think people think it's a technical challenge

[26] Pierre Nanterme

[27] Gillian R Tett, Managing Editor, US Financial Times. Davos 2017, The Fourth Industrial Revolution: Technology driven, human centred, https://youtu.be/KWT53BHd_Cw

and it's not. It's a financial challenge, ninety-five per cent of the world's population live in areas with at least have a 2G connection or more. The problem is money, the implicit cost of Facebook data if you're an average user in the United States it's a dollar a day" (P25)

"I mean some of these mature countries, the average person has a savings of $400. I mean they're one car breakdown or health care crisis away from being broke… You know Gini, you were talking about the education and the idea of massive online computer training and what we can do to initiate those that are uninitiated … if they worry about being replaced by a robot, they will be even more worried if the digital skills are the only way to findings a job" (P21[28]).

6.3.2.3.2. Net Technology Consumption

Understanding the digital divide as net technology consumption places the consideration of the divide from a technology supply chain perspective, with net technology producers in the developed world and net technology consumers in the developing world and emerging economies (P39). The population in these economies, consume these technologies because digital connectivity makes possible technological integration, however, the form of integration of people who are at the base of the pyramid is such that they derive less value from participation, they generate data with fewer returns to the data they generate. Furthermore, technology is not implemented across the globe on an equitable basis, meaning those on the receiving end do not shape how the technologies are developed, though the consumption scope can be controlled by policies and regulations (P40). The scope of regulation is however limited since digital technologies and platforms have been shifting the power of regulatory arbitration from traditional institutions of governance towards these platforms thus privatisation of public governance.

"Now how we started in Rwanda or when you see many cases in Africa, are embracing technology consuming it not yet producing sufficient technology and we have to make these two transitions, one to make use of technologies that exist, but also to be part of that production of technology rather than just continuing to consume" (P39[29])

"The countries that I operate in India, Bangladesh, Sri-Lanka, Sub-Saharan Africa, I think we will leave the AI to Mark and the Western world to deal with it, it will eventually find its way into our economies but for us, technology is not a question of if and when it got to be used now

[28] Ginni Rometty
[29] Paul Kagame, President of the Republic of Rwanda. Davos 2016, The Transformation of Tomorrow, https://youtu.be/mtXfzd53wRQ

because it's imperative that countries that I operate in and many more similar countries need to adopt fast most of the monies that the world has at its disposal needs to be directed towards technologies that will ensure that the underdeveloped countries, emerging markets adopt the use of these technologies" (P40[30])

6.3.2.3.4. Digital literacy

The concept of digital literacy to explain the digital divide was paramount in understanding how societies can shape themselves in meeting the challenges of DT such as job market participation and income distribution. According to the proponents, digital literacy is the skills to work with digital technologies, in developing technologies since those with these tech-related skills will most likely benefit from the tech-induced surplus (P21). This digital literacy spans multiple dimensions, such as phone connectivity, internet technology, digital infrastructure and software programming and development, which is proposed to be a basic skill and a good measure of digital literacy (P26). Institutions have been inefficient at increasing digital literacy in line with the changing jobs, economy and technology engendering structural unemployment, thus the lack of these skills is understood to constitute digital literacy (P26, P17). Digital literacy is a critical aspect of the digital divide that must be addressed since the skills influence the productive use of technology (P17).

"I think there is going to be an inclusion problem. There is a large part of society that does not feel that this is going to be good for their future. We have a really serious duty about this because these technologies are moving faster in time than their skills are going to change" (P21[31]).

"I think the biggest opportunity is the people who are getting into the workforce are not well trained on some of the new skills that are required. That's what I call this digital literacy, and some of the emerging areas, the academics need to focus a lot more in making the graduates highly employable and well trained" (P26[32]).

"I think that as the technology continues to advance as we've heard and the sets of skills continue to change and at the same time as there are people and companies that can't find the workers with the right sets of skills. Other workers have spent their lives and doing one kind of job where machines can now do big parts or even all of those jobs and so this is the essence of

[30] Sunil Bharti Mittal, Chairman, Bharti Enterprises India. Davos 2017, The Fourth Industrial Revolution: Technology driven human centred, https://youtu.be/KWT53BHd_Cw

[31] Ginni Rometty,

[32] C Vijayakumar

the mismatch, you simultaneously have people who are finding their jobs automated at the same time technology is creating new jobs" (P17).

6.3.2.4. DT and Income distribution

The labour market has been an important social institution in the distribution of income in the third industrial revolution, however, a high point under the third industrial revolution was the understanding that technological advances explained at least 85% of productivity, with a shift in income distribution from labour to capital. Since the 1980s, the labour share of income has been decreasing (Brynjolfsson, 1993; Flanagan and Stillwell, 2018). Wages were discussed as increasingly becoming a declining share of the income from production and wages have become an inefficient indicator of income distribution as they represent an increasingly smaller proportion of aggregate income (P12). Thus, while DT will result in an economic surplus, the distribution of the surplus will not be efficient, with the unequal distribution of income affecting the cycle of economic growth (P48). The capital displacement of the labour share of income has been seen as a constant feature of technology advance heightening with digital transformation, such that labour must transform to preserve its contribution and income share. However, the devaluation of labour under DT has adverse implications for the livelihoods of those in low-middle skilled, middle-income jobs constituting a large share of the population (P22).

"We can make any job a good job and we can recognise work, where it's for example care work and pay it a good wage, it's not about affordability. The world is three times richer than it was 20 years ago, but we are not distributing it through wages" (P12[33]).

"So, we continue to be more productive as an economy. We continue to grow, corporate profitability continues to increase, yet we do not see substantial labour increases. Or if we do, as we've seen in the last few years, job increases, we don't see wage increases at the same time" (P35[34])

".. but compensation for labour is at a 50-year low, even when you add the CEO pay in compensation is at a 50-year low and profitability is at a high… We somehow are not valuing labour the way we're valuing other parts of the economic model" (P44[35])

[33] Sharan Burrow
[34] Arne Sorenson
[35] Guy Ryder, Director General, International Labour Organisation (ILO), Geneva. Davos 2016, The promise of progress, https://youtu.be/ASsLyeZHP7Y

"Well, here is the problem, one of the things we can see, it's most clear in the developed countries is that the productivity gains are not showing up in the incomes of the average or median workers. They're showing up in that very small sliver of the population whose talents are enhanced by the technology, not substituted for it. Well, if this is the case, this is a huge problem, because as the technology takes out jobs, it takes out income" (P22).

6.4. Reconfiguring societies for digital transformation.

6.4.1. Adaptation to digital transformation

Adaptation to DT requires policy intervention rooted in economic incentives, which do not stifle economic performance, should be structurally oriented and support long-term socioeconomic solutions (P15, P30). Policies will be required in reskilling, retraining and design of lifelong learning, for instance, through the use of credit-based incentives for training. While governments and private companies including academic institutions can be instrumental, the workforce should be integrated and engaged in the shape and form of digital adoption and transformation. To work, such changes require to be implemented during the transitory period, meaning policymakers must anticipate, plan and implement policies that shape technological transformation (P30). Technology displaces jobs during structural shifts in the labour market, while reskilling and retraining will save jobs and ensure improved participation in the labour market. Adjusted social contracts, educational reform, minimum wage supports, collective bargaining, tax policies and negative income taxes were proposed as effective policies measures (P30, P22).

"Upskill the nation in France and last September we passed a law that creates new rights and a new landscape for the whole skilling, upskilling and the lifelong learning, create a system that helps companies to keep their employees and reskill massively … create a right for any of the workers or employees in France, they will benefit from a credit for training every year" (P15[36]).

"In between now and then, you have to put in systematic measures, structural policy measures to ensure that people aren't left behind and there is a cover for them. But that is something that we can come up with policies for. But that should not be the primary driver, that should be the exception. The primary driver should be that of educating, of connecting and of creating" (P30[37]).

[36] Muriel Penicaud
[37] Vishal Sikka

"If the technology is taking out those jobs and not going to replace them with others, there are things like minimum wage support, collective bargaining, who's going to bargain for the shares? How are you going to divide up the shares? It's going to depend upon workers having a voice in this. So collective bargaining, minimum wage and then ultimately, I think tax policy and longer-term, a kind of basic income or a negative income tax approach would be required" (P22[38]).

6.4.2. Educational reform

DT brings with it the demand for new skills while it also makes the majority of existing skills obsolete through digital technology substitution. To this end, there is a need for institutional capacity to produce the required skills, through changing the model of education and educational reform directed at breaking away from conventionality (P26), addressing the skills gap in education (P17) and equalisation of educational opportunities at primary school level (P26). The skills gap in education has been the reason for inequalities in income distribution since human capital, that is labour and the skills determine people's participation in the labour market, hence the negativities around the skills gap across the globe. This is more so evident between the developed and the developing countries, between children from high socioeconomic status backgrounds and those from low socioeconomic backgrounds (P30). In countries in the advanced world, apprenticeships where there are collaborations between educational institutions and business, vocational programmes and the drive to make education cheaper have been various forms educational reform has been taking. Continuous learning must necessarily focus on the skills so that people continue to be relevant in the digital economy, however, this will require massive rescaling of the educational system, with a focus on sciences and application-based learning, collaboration and teamwork (P26, P17). Educational reform must shift focus from tasks and knowledge systems that are easily replicated by machines or where advanced machines excel at but towards higher-end human skills, such as critical thinking (development in reading and writing from an early age), collaboration and teamwork, analytical thinking, interpretation, technology development, creativity and innovation and entrepreneurship (P30). However, these strategies need to be complemented with addressing deep and underlying socioeconomic imbalances that block access to educational opportunities for the majority of the population and more particularly at the household level, where access to educational resources might not make a decided impact as there are limiting conditions, such

[38] Laura D'Andrea Tyson.

as poverty, lack of access to decent housing, sanitation or modern energy and even connectivity characteristic of people under poor socioeconomic conditions (P30, P17, P26).

"I think that as the technology continues to advance as we've heard and the sets of skills continue to change and at the same time as there are people and companies that can't find the workers with the right set of skills" (P17[39])

"I think the emphasis is on continuous learning, I think as businesses we are doing a lot of things to enable and train our employees to upskills themselves and learn new things. I think it's just again a lot of relearning for people who are coming out of the educational system to learn new skills. I think it's better that we put a lot of focus in training them in the right manner so that they're highly productive when they hit the workforce" (P26[40])

"And if we equip them with education and if we especially educate them in the right way about the way the world of the future is going to be, we equip them, all evidence indicates that every innovator that showed up out of nowhere and made something great happen did it based on a culture of making, based on a culture of experimentation, based on taking risks, adapting, why don't we teach these skills on a massive scale?" (P30[41]).

6.4.3. Addressing initial conditions

Countries in the developing world and emerging economies have mostly experienced being left behind in the third industrial revolution, failed to harness the power of that technology and did not develop skills related to that technology which have been as platforms to skills of the fourth industrial revolution. In addition to this, the societies suffer from disparities in socioeconomic development, known as the physical divide, there is, therefore, a need to address the physical divide among all socioeconomic classes, particularly among women (P39). If unaddressed these initial conditions or the physical divide will exacerbate the inequalities of the digital divide (P39, P11). There are inequities in health, education and in other aspects of socioeconomic welfare. In the developing world, women are less likely to be educated than men, less likely to be literate, have less access to digital technologies including data, which means that policies that promote DT will likely benefit men more than women (P39, P11). People with no adequate access to basic infrastructures will not use digital connectivity productively, since learning opportunities are not the same for people under different

[39] Erik Brynjolfsson, Davos 2016, Making digital globalisation inclusive
[40] C Vijayakumar, Davos 2016, Making digital globalisation inclusive
[41] Vishal Sikka, Davos 2016, The promise of progress.

socioeconomic conditions, particularly those with no secure housing, exposed to severe weather conditions, they cannot develop the critical skills such as entrepreneurship which can make them thrive in a world of DT (P11). There is simply no access to internet technology that will build sanitation facilities, secure housing, or produce the food needed to bring physical development to households under various forms of deprivation (P11). The existing economic arrangements upon which the technologies are adopted will influence the outcomes, and the current settings have resulted in economic vulnerabilities for many, such as having a larger proportion of the global workforce, not having access to secure work, those in the informal economy having no rights, social protection and no minimum wage regulations in place supporting them (P11). The constraining socioeconomic conditions that limit households and individuals are exacerbated by the structural arrangement of the economic system such as exploitative and impoverishing supply chains, enslaving of the workforce and disintermediation between the workforce and the mechanisms for wealth creation (P11).

"But another lay is that say among the people say in Rwanda or any other country, within the country is another divide in a sense that you have women left behind in many cases well it is education or their health and so on. So, if they are left behind in other instances, for example, education then these are the ones who are deprived as far as the digital divide is concerned" (P39[42])

"Well, you know already if you just look at you know smallholder farmers, not even talk about poverty but those who work informally essentially live hand to mouth, they are already squeezed within global supply chains. I believe that algorithms, new technologies are not only going to make that more severe that you know is that the plight of poor people"

"I mean there is a narrative around connecting the world right, I mean Facebook's big thing is let's give everybody internet, they will miraculously become entrepreneurs, access to information and I mean on one level that's true but against a backdrop of not having infrastructure it's not going to help I mean 65 million families in India in the rural sector alone live in houses which are not secure, they are essentially prone to destruction by weather, so you bring the internet into that okay it helps on one level but it's not going to promote the kind of economic development that people think" (P11[43]).

[42] President Paul Kagame, Davos 2016, The transformation of tomorrow.
[43] Eric Stryson, Global Institute for Tomorrow, 2017

6.5. Discussion of findings and literature integration

In section 2.3.1, it was argued that the effective labour and capital investments in the economy are those associated with the technological arrangements existing in the economy or envisioned and maximize the nation's resource endowments. The technological transformation was argued to be beneficial to a society if it intensifies the society's use of its abundant resources, that exhibit sustainable growth, with investments in labour to improve the developing technology as technologies are developed and applied to solve a nation's productivity problems (Romer, 2011; Jones, 2019).

The quantitative analysis of skills and their distribution among the South African population shows that under the third industrial revolution, policies directed at transforming the distribution of skills have not been instrumental in equalising skills among the population (5.9). Moreover, the larger proportion of the population is predominantly at a high risk of experiencing technology-induced displacement as they possess low to middle-level skills. Highly skilled individuals were predominant in the White and Asian/Indian population groups, which are a minority proportion of the South African population. This means that the abundant labour resources available in the majority Black population risk being made redundant, which will increase income inequality and loss in employment among the larger population segment. Thus, DT will be sustained by a very small segment of highly skilled people, while the majority of the people are incorporated adversely in the developing arrangements for production and exchange.

The qualitative analysis showed that the source of technology-induced job displacement is advancement in technology displacing some aspects of labour, some routine and knowledge work, through automation, 3D printing, robotics and artificial intelligence (6.3.2.1). The permeation/diffusion of technologies in social and economic life implies the centrality of technology in social and economic life. This will require skills that are presently in short supply thus creating structural unemployment. The nature and continuation of structural unemployment brought about by technology-displacement of labour will be determined by the pace and evolving nature of digital transformation, which was argued to be characterized by speed (6.2.1.4). In the discussion (section 2.3.2), technology displacement of labour was argued to be the outcome of the general-purpose technology, which shapes the nature of physical and human capital requirements in the economy. Human and physical capital endowments that services technology or are aligned to the developing technology platform remain relevant, while those which are not, experience marginalisation. This was argued to result in the development of unemployed labour and capital resulting in factor-induced or structural unemployment (2.3.2) (Jones, 2019). The qualitative analysis converges with the general ideas thus discussed in the theoretical model, of the sources and forms of unemployment.

It was argued that the larger the stock of human capital the general-purpose technology depends on, the more the employment of human capital will be observed in the economy. The less human capital the technology absorbs, the less employment of labour (2.3.2). Digital technologies rely on data on human activity in the development of technologies and their applications, the technologies model human activity and replicate it (6.3.2.1). Much of this data is collected through the software platforms without human agency, and thus without compensation. This data is then used by a small group of highly skilled people to generate huge returns (6.3.2.1). Thus, the technologies heavily depend on the unpaid contribution of human capital, while employing increasingly a small number of highly skilled individuals, who are in short supply in most of the developing world, South African in particular, as the quantitative analysis demonstrated (5.9). The unpaid contribution of human capital is significant under DT strengthening the argument for the continued decline in the labour share of income (Flanagan and Stillwell, 2018; Jones, 2019).

The EGM proposes that income inequalities are explained by or are the outcome of differentials in human capital and access to physical capital. Those who innovate and develop technologies are protected by patents and intellectual property and other incentives thus restricting competition in the knowledge sector to stimulate growth although this leads to disparities in the economy (Crafts and Woltjer, 2020). Improvements in standards of living are not automatic but rest heavily on social infrastructure capability and technological congruence. By social capability, reference is made to the population's ability to assimilate new technology or the ease with which the general population adapts to the new technical arrangements in their economic and social life (Crafts and Woltjer, 2020). Thus, human capital differentials have a significant influence on the shape of the resulting socioeconomic outcomes. The quantitative analysis showed that highly skilled individuals (5.9.1), had access to more secure forms of employment (5.9.2) and lived in better socioeconomic conditions. In the qualitative analysis, DT and its processes were argued to exacerbate these initial conditions, with job gains going to be outpaced by job losses coupled with the displacement of middle income, middle-skilled jobs, such that the socioeconomic disparities will become more pronounced (6.3.2.1).

The EGM further proposes the central role of the labour market as the redistributive mechanism, with the assumption that people can readily access training and incentives to upskill themselves and participate. However, the labour share of income has been falling due to the increasing importance of digital technology, undermining the efficiency of the labour market as a redistributive mechanism, as labour wage increasingly represents a small share of national income (Flanagan and Stillwell, 2018). The qualitative analysis converged on the same issue with participants alluding to the falling share of income in the form of wages and the inefficiency of the labour market as a redistributive mechanism (6.3.2.4: P12, P20, P35). The conclusion was that digital technologies have been enabling countries and individuals to generate increased income however the distribution of this income is going to be uneven across countries and individuals in different economic strata and different regions within countries, the dislocation effect. As machines displace low-middle income jobs, urban geographies will lose their competitiveness as labour hubs unless advantage is gained through reskilling and training programmes, yet this loss of labour competitiveness will result in income and welfare losses worsening socioeconomic conditions of those regions (6.3.2.4). Labour as such must transform so that its contribution may be preserved.

The EGT proposes that the income differentials in society can remain because poor people however willing to learn and invest in social capability are not capable of making the same progress as the rich for want of equal means of instruction, good models and developmental experience (Cavusoglu and Tebaldi, 2006). Education and training differentials have been discussed in the literature as contributing to the inequalities in labour market outcomes in South Africa. The structure of skills and labour market participation in South African is the outcome of educational and training institutions, with highly unequal access and outcomes (Branson and Leibbrandt, 2013; Kimani, 2015). The quantitative analysis showed that the majority of South Africans experience institutional exclusion in educational institutions and lack access to developmental opportunities such as financing health, education and other essential services (5.7). This state of exclusion is reflected in the labour market outcomes, in the differentiated profile of job competency and other skills (5.9.1). DT does enable equalisation in access to financial inclusion through mobile-based applications and platforms. However, equality and socioeconomic welfare largely rest on access to technology, developing and shaping it to meet the needs of the society and the capacity to work with the technology at a productivity level (6.3.2.4). These capabilities are in a very limited supply in South Africa, at least according to the analysis of the NIDS data.

However, there are no limits to the scope of innovation, creativity, design and collaboration with the digital technology platform, implying with well-designed interventions that equip the population with the needed skills, the scale of employment and welfare improvement can be significant. This follows from the arguments of the endogenous model that a factor will continue to contribute to growth as long as the influential factor continues to grow and, in its growth, remains positively relevant to the evolving technical apparatus of the economy (Romer, 1994). While analysis of skills using the job competency index showed that the needed skills have been in short supply in South Africa hence the inequalities in income distribution. The upskilling index showed further the challenges around the transformation of the labour market to provide the required skills for the fourth industrial revolution, upskilling and reskilling. Across the five waves of the NIDS data collected, the majority of the population were insecurely employed, with significant shares of unemployed, economically inactive and discouraged workers among the African population subgroup. These individuals have been demonstrated in the analysis presented in 5.8 to be living under limiting socioeconomic conditions, and hence cannot afford financing personal development in education and other forms of human capital development. Thus, the needed human capital presently in short supply in South Africa will need to be developed on a large scale according to the model in this study yet the capacity is not going to be possible through the individual agency, for the outcomes have been adverse as demonstrated in the quantitative analysis (5.9).

Income distribution within an endogenous system was argued to be determined by the extent to which changes in technology generates changes in income and the nature of income distribution (Crafts and Woltjer, 2020). Access to new skills and new forms of physical and intangible capital investments that align with the new technological arrangements shape the forms of income distribution. Digital technologies such as artificial intelligence, 3D printing, robotics, nanotechnology, big data technologies and autonomous systems require new forms of capital and new human capital skills (OECD, 2017; Sousa and Rocha, 2019). The quantitative analysis showed that over a longer horizon, interventions and institutional arrangements have not been instrumental in developing the needed skills over a larger proportion of the population in South Africa, with the skills aligned with these technologies being concentrated among a few, hence the inequalities in income and capital formation in the country (5.9) (Kimani, 2015; Flanagan and Stillwell, 2018). Higher-end human skills such as critical thinking, problem-solving, design thinking, analytical thinking and technology development are needed. Access to mobile computing has been robust across the five waves of the NIDS data, which spans over a decade-long period, which is instrumental in accessing mobile platform based digital technologies hence improving access and integration, however, objective transformative change requires shaping the development of technologies and aligning them with the productivity needs of the people themselves (5.3.1). Thus, the increase in access to digital technologies observed in the quantitative analysis is consistent with the qualitative finding of net technology consumption, which means the majority of people do not shape how the technologies they use affect their everyday lives. Furthermore, a highly skewed income distribution profile is likely, which will present difficulties with designing the right interventions because of the new arrangements and mediation of social relations and work.

According to the endogenous growth model, the production of new knowledge and ideas depends on the quantity of physical and human capital devoted towards research and on the level of technology--since existing knowledge discoveries shape the discovery and development of future ideas (Romer, 2012). Human capital generates the knowledge that creates capital and its applications as solutions to the problems of society. Following this line of thinking, the interventionist policy must be directed at influencing factors that influence the generation of human capital and its contributory role in generating productivity and income growth. The deliberate actions of individuals through their institutional provisions bring about economic growth by transforming the technical platform of the economy shaping economic activity, the more they shape it, the greater the possibility for sustained economic growth (Jones, 2019). The qualitative analysis showed that while DT brings about income growth, developing countries do not have the capacity for self-sustained growth as they are net technology consumers since they do not shape the development of the technological platform to meet the needs of their societies (6.3.2.3.2). The analysis showed that net technology consumption places developing countries at the lower end of the scale with very few returns comparable to their contribution in terms of data, even though the societies become technologically integrated. Since they do not shape the technologies thus consumed in their ideologies or applications, some technologies may lack real impact on improving the productive lives of the poor, since they are not designed with their needs in mind (6.3.2.3.2). The quantitative analysis of the digital index showed that among the poor increased access to technology has been associated with increased access to mobile phones, which do not necessarily enable users to engage in technology development, while access to higher-level devices such as computers and computer skills have been the preserve of those from high socioeconomic backgrounds (5.3.1). The sustainability of DT can be a challenge due to the low base of digital proficiency across the South African population as shown by the quantitative analysis (5.9). This coincides with the proposition by Lucas (1988), that human capital, the skills and knowledge aligned with the changes in technology enables the production of more knowledge and increased productivity (Romer, 1994).

It was argued further that as long as the economy continues to invest in knowledge development and capital that labour can work with, productivity improvements can be sustained creating income growth and employment. However, the important knowledge is that which is connected with the general-purpose technology platform (Jones, 2019; Romer, 1994). Among the salient findings from both the qualitative and the quantitative analysis, was that the development of higher-end skills such as critical and design thinking, collaboration and analytical thinking, is influenced by the socioeconomic conditions of the people, the physical divide. People occupied with solving issues connected with lower-level living conditions do not have the time to think and develop the technology. According to the quantitative analysis (5.7), the majority of South Africans, lack access to developmental opportunities such as credit access, health insurance and experience limited access to education and training directed towards higher-end skills development. In the qualitative analysis, it was noted that the physical divide or socioeconomic differences do explain why technological advances are found among individuals who live in socioeconomic conditions of the top 10% (6.3.2.4). Thus, net technology consumption is likely going to be a key feature of DT in South Africa and other developing countries, with the change in fortunes depending greatly on the efficacy of policies directed at addressing the physical divide and enabling individuals to begin to engage in analytical thinking and technology development.

In the qualitative analysis, it was argued that technology spill overs are not limited only to the technology-related sectors, since technology has been seen to power even sectors that are not technology orientated and even increase their productivity. Thus, the whole society even sectors not directly connected with technology tends to benefit, although the state of the socioeconomic conditions will determine whether the society participants have the entrepreneurial skills, the critical thinking or analytical skills that enable them to master the skills that enable them to utilise opportunities of the digital technologies (6.3.1). The quantitative analysis demonstrated that there is an existing skills' divide that marginalises a larger proportion of the population from participating and sharing in the surplus of digital transformation. It was also observed that the socioeconomic conditions prevalent for the greater population proportion limit human development (5.9, 5.8). Thus, while digital technologies can increase access to digitally provided skills, digital interventions in production, the skills divide will likely remain due to limiting socioeconomic conditions which determine how technologies affect individuals and households. People will best engage in higher-level activities if they have material access to interventions that can address their physiological conditions, such as secure housing, health, nutritious food and elimination of poverty.

6.6. Chapter Summary

DT is understood as a digital ecosystem for innovation, as the fourth industrial revolution and business model transformation. In all these conceptualisations, the driving force is economic productivity. Technologies driving DT have a spatial dynamic and ideological context that creates conditions for digital inequalities even though they can be extensive benefits and opportunities for societies across the globe. Societies will thus require institutional restructuring, policy intervention and skilling as well as addressing the limiting physical divide to ensure digital inequalities are not exacerbated. In the next chapter, these results and those of Chapter 5 are integrated and discussed.

CHAPTER 7: CONCLUSIONS OF THE STUDY

7.1. Orientation and outline of the purpose of the study

The study has attempted to provide a comprehensive inquiry of the relationship between digital transformation, its conceptualisation and effects on the South African society based on the socio-economic characteristics and skills profile of individuals. The direction adopted in the research study of examining digital transformation, its characteristics, processes and drivers in light of the socioeconomic characteristics and skills profile of individuals was driven mainly by the absence of such an analysis for South Africa. Some studies examined in the extant literature have focused on institutional capacity (Manda and Backhouse, 2017) and digital policies (Brown and Czerniewicz, 2010; Oyedemi, 2012) in South Africa with the majority of studies focusing on the advanced societies in the developed world (Afonasova *et al.*, 2019; Balsmeier and Woerter, 2019; Strohmaier, Schuetz and Vannuccini, 2019; Verhoef *et al.*, 2021). This study performed an analysis of digital transformation using a longitudinal panel dataset to examine the digital divide across socioeconomic characteristics and skills profiles of South Africans to provide a context for understanding and discussing the effects of digital transformation, its characteristics and processes.

7.2. The Methodology of the study

The quantitative nested sequential mixed-methods study was used in the investigation of socioeconomic characteristics of individuals and the shape of digital transformation. The quantitative nest nature of the model implies that the study was built on the quantitative analysis, the results of which informed the aspects which were the key focus of the qualitative analysis in light of the theoretical foundations of the study. The quantitative analysis focused on the 5 waves of the NIDS data in which index variables measuring the digital index, socioeconomic characteristics, social inclusion/exclusion and skills of individuals were assessed in descriptive analysis and inferential analysis using a multiple linear regression model. With the results of the quantitative analysis the sequential aspect of the mixed methodology design, required collection, preparation and analysis of the qualitative data to find explanations for the effects of digital transformation on observed characteristics in the quantitative analysis. The sequential nature directed the aspects that were of paramount importance in qualitative analysis without recourse towards theoretical saturation as in grounded theory methods for theory building. Thematic analysis was used at two-level, firstly, semantic analysis of the data broadly grouping the data based on a coding template and secondly, latent thematic analysis based on the results of the semantic analysis. The integration of results of this methodological approach is presented in section 6.5 and provides a discussion of the connections between digital transformation and socioeconomic characteristics of individuals in light of the theoretical foundations of the study.

7.3. Summary of the results

Question 1: Given that human capital is central to individual adaptive potential in digital transformation, how do observed socioeconomic conditions affect the observed patterns of human capital development?

The study showed that observed socioeconomic conditions influence the capacity of individuals to develop themselves. While, DT can make access to learning and developmental aids possible, people with less secure housing, low nutrition and experiencing social exclusion cannot learn at the same pace as those in better physical settings. The limiting socioeconomic characteristics typical of the larger proportion of South African households as shown in the analysis is contributory to the highly unequal human capital and labour market participation. Furthermore, the skills required to actively participate in a digital workplace require investments that are not available to low socioeconomic households, critical and design thinking, innovation and entrepreneurial skills and creativity requires not only financial resources, institutions but also time, which low socioeconomic households do not have.

Question 2: How will DT affect the welfare of individuals and households in their societies?

The study showed that where DT occurs in a broadly under-skilled and institutionally weak society, its adverse effects such as labour displacement and exacerbation of the physical divide are heightened. However, where there are effective institutions, policies and the population have the requisite skills and competencies, the capacity of the transformation to effect positive outcomes is significant.

Question 3: What are the observed interactions between DT and socioeconomic conditions?

It was demonstrated in the study that socioeconomic conditions determine access to digital technologies and digital literacy. While the study examined access to mobile computing, computers and internet and digital skills, it observed that households with better socioeconomic indicators such as access to developmental opportunities, higher household stability and productive assets among other indicators had access to both advanced digital skills and digital assets than those with poor socioeconomic indicators. It was concluded that these inequities in the physical divide will be deterministic of outcomes of digital transformation.

Question 4: What are the expected challenges and opportunities of DT for individuals and households in South Africa?

In South Africa, the physical divide creates a weak platform for beneficial DT since lack of skills, high risk of displacement places individuals at high risk of marginalisation. The existing digital divide implies that increased access to platforms will not be beneficial to many since to participate productively, individuals require skills and competencies. The potential challenges of DT to South Africa, are technology-induced unemployment, strengthening of the existing physical divide, worsening of the income distribution leading to a potential more unequal society. Loss of jobs may engender income losses resulting in low demand for goods and services. Platform work is insecure and heightens precariousness. South Africa like other emerging economies is likely to be a net technology consumer, meaning that while business efficiency might improve, the transformation might not be inclusive of the context of the local economy, in its resources, ideology and future sustainability. The richness and diversity of the country and its society are not embedded in the technologies thus might not influence the productivity needs of the people.

Technology on other hand is deemed a net jobs creator and can increase the incomes of countries thus making possible large-scale development. The displacement of low-middle skilled jobs can spur focus on high-end skills, thus making societies more productive and competitive. Technology was argued to lead to total factor productivity as it powers jobs even in non-technology related sectors, such as enabling people to access markets for goods and start online businesses and reach markets not before possible. Digital technologies can solve governance needs on a massive scale, providing biometric systems, surveillance and improved security and curbing inefficiencies thus improving societies. Finally, the technologies can potentially eliminate spatial disadvantage through increased digital connectivity leading to the elimination of disenfranchisement and marginalisation.

Question 5: How can the expected outcomes of DT be shaped so that welfare gains can be maximized and welfare losses minimized?

Based on the results of both the qualitative and the quantitative analysis, South Africa will need to design interventions directed at addressing the existing physical divide through increasing access to personal development and large-scale skilling and reskilling of the working population. There is a need for programmes to address the digital divide particularly digital literacy which can improve people's participation in the changing environment. Other interventions included educational reform, alternative platforms for recognising skills than traditional institutions, reinvigorated social contracts and addressing the gendered differentials and their negative impacts.

7.3. Key contributions and implications of the study

The effect of DT on the welfare of South Africans will be determined by the state of the physical divide in which individuals subsist. Observed socioeconomic conditions influence the state of human capital development. Individuals in stable socioeconomic households have a higher likelihood of possessing high-end human capital competencies than those from lower and unstable socioeconomic households. The quantitative analysis showed more inclusion and access to digital technologies for individuals from stable socioeconomic households. This could be attributed to the ability of high socioeconomic households to be able to finance the acquisition and development of high-end skills such as design thinking, entrepreneurial ability, creativity and innovation associated with access to institutions of higher learning. In South Africa, technology access, socioeconomic and social exclusion assumed a resilient group profile, with poor indicators for the African population group comprising the larger population share. This group has the lion's share of poor human capital development, concentrated in low-middle skills and sectors at high risk of technology-induced displacement as shown in the analysis. The observed pattern of socioeconomic conditions influences human capital which aspects shape the digital divide, hence the pattern of inequalities associated with digital transformation.

Observed pervasive access to mobile devices across the population aligns with increased access to mobile-based aspects of DT with beneficial consumer end participation in financial inclusion and some health applications. However, these forms of participation bring relatively lower returns. Development of technologies, their ideological premises and shaping them to one's productivity requirements are largely absent in South Africa even among the small proportion of the population with high-end skills and access to other digital assets and skills. Thus, DT will be largely associated with net technology consumption and its adverse socioeconomic implications.

Technologies driving DT are likely to displace human agency in economic activity, and it is projected that this trend will grow with increasing technology evolution. Initially, this displacement will be experienced in routine work and some aspects of knowledge-based work. This implies that the advantage of countries as low-middle skilled labour hubs will disappear, as technology displaces such jobs, such that a sustainable policy perspective for long term welfare will be reskilling and skilling of the labour force towards high-end skills. Technology displacement of jobs reduces the labour share of income, with redistribution of income towards capital share, such that e the fall in labour income across the economy may negatively affect demand for goods and services. However, it was also observed that countries with high per capita capital ratios have low employment rates showing that DT may yield more positive effects on society if the transformation is affected with robust social institutional foundations. The majority of South Africans live in low socioeconomic conditions, experience social exclusion, and are concentrated in low-middle skilled jobs at risk of displacement. Technology induced job displacement will be greater where DT occurs within the context of a broadly under-skilled labour force.

In the quantitative analysis (5.10), there was a strong association between socioeconomic conditions and access to digital assets. Households with sub-indexes for poor socioeconomic performance showed only access to mobile devices, with little or no digital skills. The physical divide shown in poor socioeconomic performance determines the digital divide and its consequences on future welfare. With the entrenched physical divide, DT will likely exacerbate existing socioeconomic disparities and marginalisation of those not able to access digital technologies and the skills to use them.

DT technologies rely on data flows in all aspects of society and the economy. The data is the lifeblood of application development and optimisation, providing the basis for better decision making, governance and technology development. There is co-production of content and data between platform developers and society, yet the contribution of societal participants is unremunerated while developers who use the data to develop applications make significant returns. These inequities in income distribution are exacerbated by network effects and the physical divide.

7.4. Conclusions of the Study

The study has demonstrated the existence of a digital divide of long continuance and resilience in South Africa and manifests along racial lines. The racial differences in the distribution of the digital index are reinforced by differences in access to developmental assets, institutions, training and development, finance and household level assets and infrastructure. In the decomposition of the digital index implemented in the study, it was seen that racial differences were not important nor socioeconomic characteristics in the comprehensive digital asset index which was explained to be characterised by a high loading of access to digital smartphones, the regression models accounted for a very small share of the variation in the index. Various studies were noted to have focused on ICTs for development, yet concentrated on access to smartphones and similar communication devices (Conradie D.P., Morris C., and Jacobs S.J., 2003; Diga, Nwaiwu and Plantinga, 2013; Adera, Waema and May, 2014). There is a very small variation in access to digital smartphones based on socioeconomic characteristics, and the MLR models used in this study accounted for a very small share of the variation requiring new surveys to collect targeted data, this was also recommended in another study (Bornman, 2016).

The study showed that differences in access to advanced digital technologies such as computers and internet access, advanced computing skills and basic computing skills were strongly influenced by population grouping. The MLR models across the 5 waves of the data explained at least 50% of the variation in each case based on the socioeconomic characteristics, social inclusion/exclusion and skills profiles of the individuals. Thus, differences in access were explained by individual dynamics based on the explanatory variables. Socioeconomic characteristics, social inclusion/exclusion (access to developmental opportunities, institutions and financial markets) and skills are important aspects in explaining the access to these indexes. Digital transformation processes are associated with this group of sub-indices of the digital index, showing that the existing differences in the socioeconomic characteristics and skills among individuals will likely be exacerbated as digital transformation advances.

The study in the descriptive analysis of the quantitative data also demonstrated a sectoral shift in the skills profile of individuals across population groups with a comparison of wave 1 and wave 5 showing that Africans were concentrated in primary occupations requiring low skills when compared to the skills profiles of Indians and Whites who showed a concentration in the high-end service skills. This was among some of the important findings in the study given the structural shift in sectoral importance and overall contribution to GDP as a report showed the growing importance of the service sector of South Africa accounting for a large share of contribution to national income (StatsSA, 2012). Thus, the structure of skills distribution masks the observed pattern of the income distribution. An intensification of sectoral differentiation and contribution to income under digital transformation will likely exacerbate the income differentials and deepen socioeconomic and social inequalities in South Africa. An earlier empirical study also observed similar outcomes, of deepening social inequalities due to digital change as more individuals are left out for lacking the requisite ICT skills and competencies (Brown and Czerniewicz, 2010). That such findings can be confirmed to hold in a study a decade later that shows the resilience of the digital divide in South Africa.

7.5. Recommendations

Policies needed to help individuals circumvent the physical divide

The quantitative analysis demonstrated the existence of a resilient physical divide manifesting through socioeconomic characteristics, social exclusion and lack of skills among the African population group at large. The majority of South African do not have the physical capacity to develop the needed skills and competencies that will enable them to participate in the digital economy. Limiting socioeconomic conditions such as poor access to household level infrastructure, lack of income and marginalisation through social exclusion from institutional participation such as labour market participation, access to developmental opportunities and access to capital markets. Digital transformation processes have been demonstrated in this study and other studies to exacerbate the existing social inequalities. There is a need for policies that enable individuals to upskill and obtain the needed digital skills through directed investments that enable the individuals to circum-navigate the limiting conditions of the physical divide they exist in. These investments have been shown in other countries to have positive returns in investing the labour force and youth in particular with the needed digital skills.

Incentives and directed investment in skilling individuals particularly youths.

In France directed incentives paid to people for enrolling in training for a list of skills targeted towards digital transformation and government level directed investment in human capital development are avenues for upskilling and skilling at a very large scale. In the programme upskill France, the government committed 15 billion euros over 5 years, to massively train young people and hence reduce youth unemployment. Such a programme can work for South Africa to curb the high youth unemployment rate (Graham and Mlatsheni, 2015; Ismail and Kollamparambil, 2015) and at the same time ensure that the youth population have the skills needed to meet the labour demand of tomorrow. Incentives have also been advocated such as directed tax credits to companies that actively engage in programmes to upskills and train the youth in the needed digital skills. Tax credits specifically directed towards human capital development can be effective to redirect focus towards the needed skills. Directed incentives towards individuals who take the initiative to upskills and invest time and energy in the acquisition of digital skills. The government needs such a programme directed at promoting individuals taking initiatives in training and development in the needed skills, such instrumentation will create autonomy among the individuals. This will require immense public capacity which at present is facing challenges through corruption and incompetence and mismanagement of public funds (Serfontein and De Waal, 2015; Munzhedzi, 2016). The combined use of directed economic incentives for digital skills acquisition, upskilling and reskilling and access to developmental opportunities are interventions that are needed to address the existing lack of digital skills among South Africans.

Need for integrated reporting to help trace key social indicators and digital metrics

To effectively plan for digital transformation, South Africa requires data streams that will enable planners and policymakers to effectively track changes in key social metrics and skills. There is a need for reporting that tracks key social metrics linked with a developed measure of the existing physical divide. Firms must not only report their financials but there must be integrated reporting that focuses on actions that have been taken in addressing key social metrics directed towards addressing the gap in skills and socioeconomic challenges. There is therefore a need for the development of a social metric that tracks the effect of the physical divide on digital index and a mapping system so that changes can be tracked and the effect of instruments can be assessed.

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APPENDIX 1: Ethical Exemption Letter

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

Mr Tawonga Rushambwa (210546078)
School Of Built Env & Dev Stud
Howard College

Dear Mr Tawonga Rushambwa,

Protocol reference number: 00012566
Project title: Digital transformation and its effects on socioeconomic outcomes in South Africa: A Micro analysis of Digital Transformation on economic and social welfare

Exemption from Ethics Review

In response to your application received on , your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]

Prof Catherine Grace Sutherland
Academic Leader Research
School Of Built Env & Dev Stud

UKZN Research Ethics Office
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
Website: http://research.ukzn.ac.za/Research-Ethics/

Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

INSPIRING GREATNESS

APPENDIX 2: Example of Cronbach Alpha and Kaiser-Meyer-Olkin Measures of Sampling Adequacy

Table A2.1: KMO measure for sampling adequacy for Digital Asset Index

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)

Variables	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Telephone1	0.4278	0.2859	0.2453	0.2780	0.2629
Telephone2	0.1197	0.1422	0.1185	0.1225	0.0839
Telephone3	0.3738	0.4059	0.4207	0.4774	0.4469
Smartphone	0.4521	0.4551	0.4656	0.5182	0.5033
Satelite Access	0.8114	0.7871	0.8201	0.8251	0.8712
Computer Acc	0.6639	0.5402	0.5455	0.5817	0.5420
Computer Lt1	0.6185	0.5318	0.5362	0.5613	0.5140
Computer Lt2	0.6506	0.5266	0.5025	0.4865	0.3902
Internet Access	0.8246	0.7377	0.8111	0.8270	0.8194
Overall	**0.4920**	**0.4419**	**0.4564**	**0.5191**	**0.4945**

Source: Own computations using NIDS Dataset

Table A2.2. Cronbach Alpha and KMO measures of sampling adequacy for Upskilling Index

NIDS WAVE	**Wave 1**	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**
KMO	0.2384	0.2372	0.3864	0.3746	0.3629
Alpha	0.7202	0.5443	0.5813	0.6599	0.6265

Source: Own computations using NIDS Dataset

Table A2.3: Cronbach Alpha Computations for Social Exclusion Index Construction using PCA.

NIDS Wave	**Wave 1**	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**
Cronbach Alpha Statistic.	0.7345	0.5743	0.6349	0.8698	0.8569

Source: Own computations using NIDS Dataset

Table A2.4: Job Competency Index measures of sampling adequacy in variable construction

NIDS WAVE	**Wave 1**	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**
KMO	0.1557	0.1469	0.1490	0.1528	0.1509
Alpha	0.5605	0.6210	0.6467	0.6732	0.6598

Source: Own computations using NIDS Dataset

APPENDIX 3: National Income Dynamics Study Data Access.

DataFirst
Private Bag, Rondebosch 7701, Cape Town, South Africa
School of Economics Building, Middle Campus, Rondebosch

13th February 2020

To Whom it May Concern

PERMISSION FOR TAWONGA RUSHAMBWA TO DOWNLOAD PUBLIC ACCESS NIDS DATA FROM DATAFIRST'S OPEN DATA REPOSITORY

This is to confirm that Tawonga Rushambwa of Howard College at the University of KwaZulu-Natal has permission to download the public access data from the National Income Dynamics Study 2008-2017 from DataFirst's Open Research Data repository and use the data for his research.

This is also to request to UKZN research administrators who request such permissions to familiarise themselves with ethics requirements for the use of secondary data held in research data repositories. The point of these institutions is to provide seamless access to primary data for research. Such repositories are set up worldwide to relieve academics of the tasks of obtaining permissions from data owners for use of individual datasets, which can impinge drastically on their research time.

Managers of internationally certified repositories like DataFirst have already done the work of preparing anonymised versions of the data and obtaining permissions to place the data in the public domain. Data in the public domain may be used by your staff and students without permission.

Yours sincerely

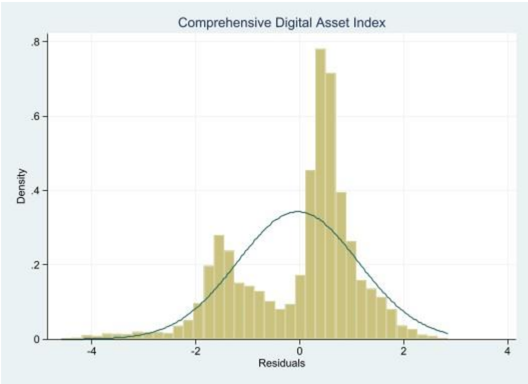
[redacted]

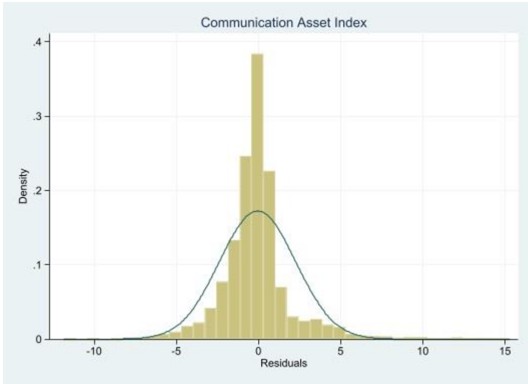
Lynn Woolfrey
Manager, DataFirst
University of Cape Town

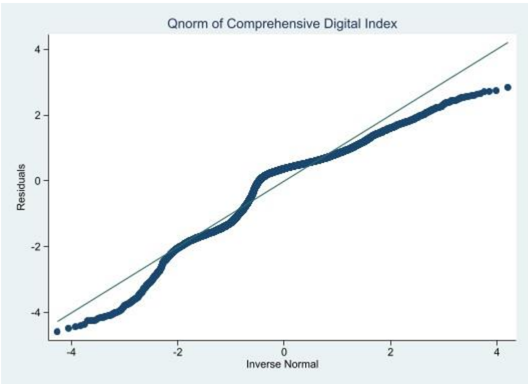
We strive for global excellence in research, teaching, and the application of knowledge to the challenges confronting Africa and the wider world.

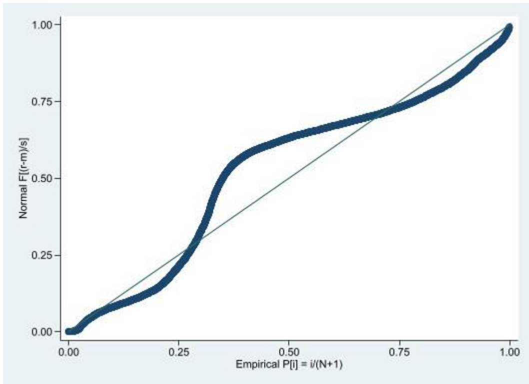
APPENDIX 4: MULTIPLE LINEAR REGRESSION DIAGNOSTIC PLOTS

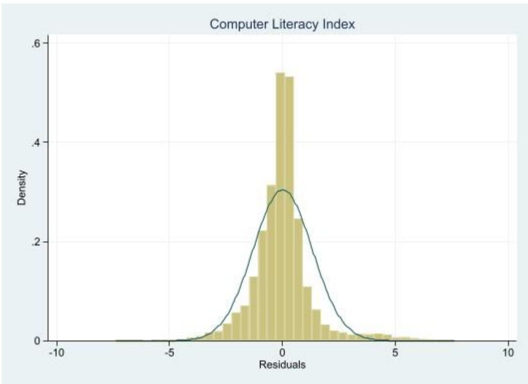
1. Regression Diagnostics Plots of Residuals Wave 1

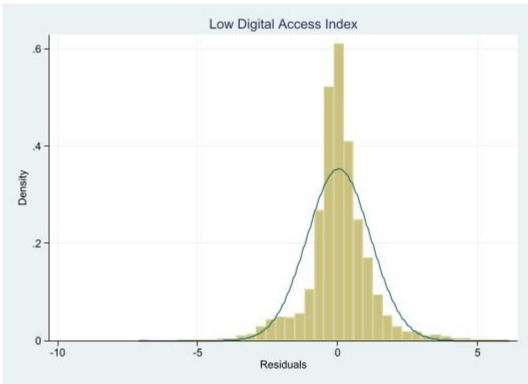


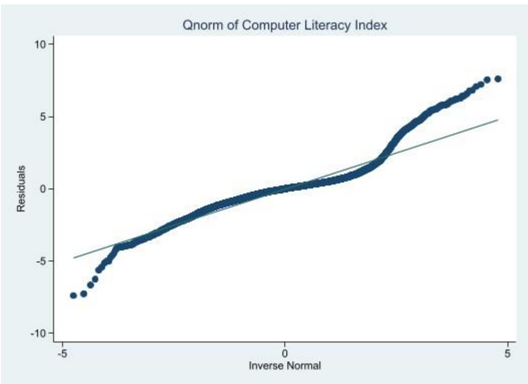


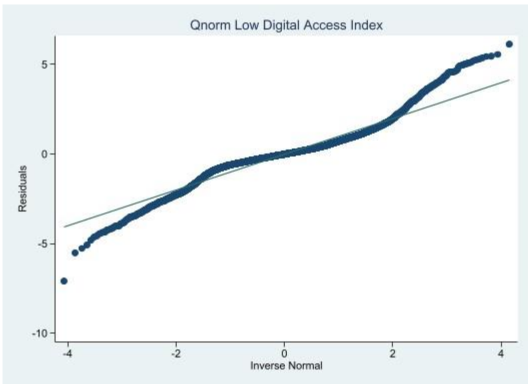




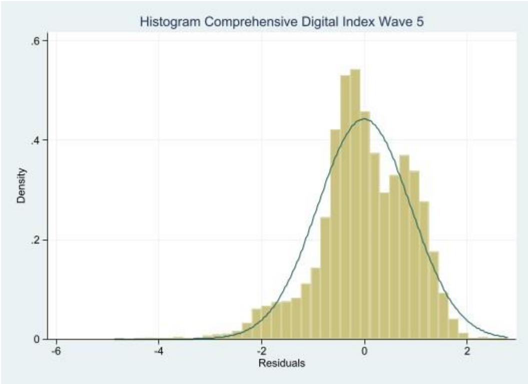


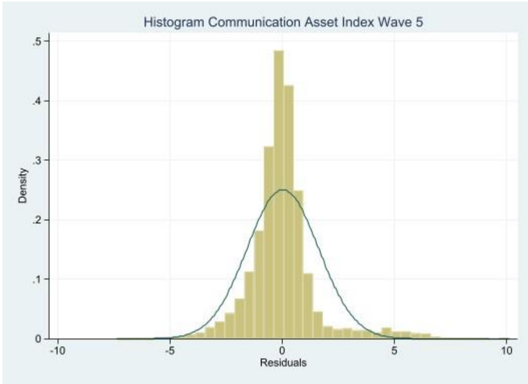


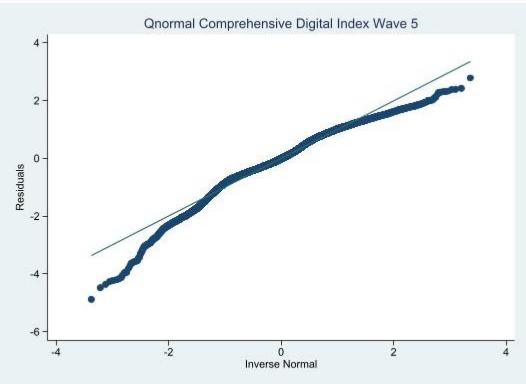


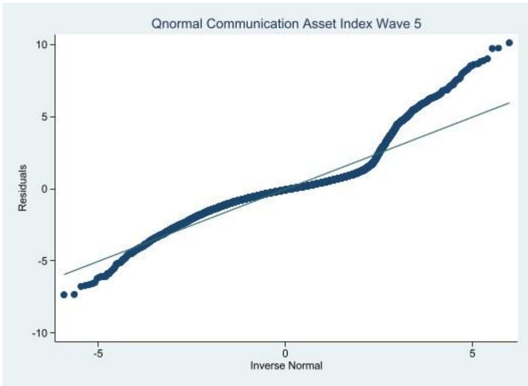


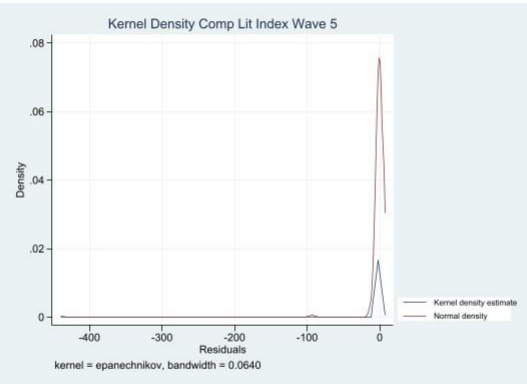
2. Regression Diagnostics Plots of Residuals Wave 5.

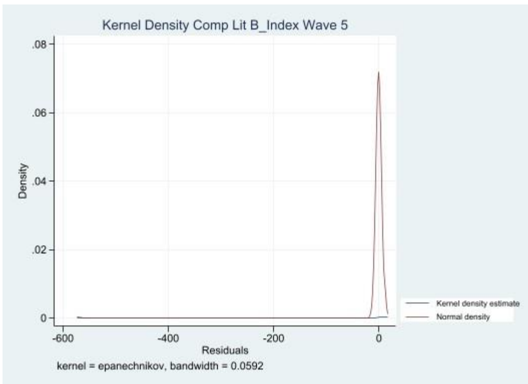


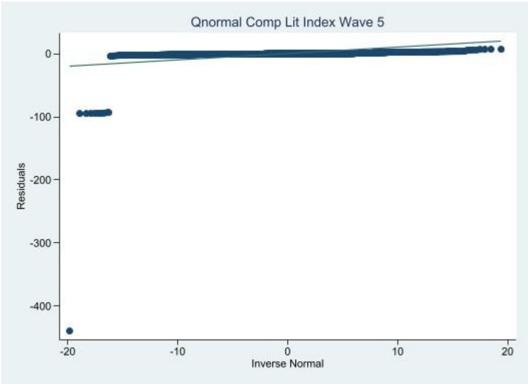


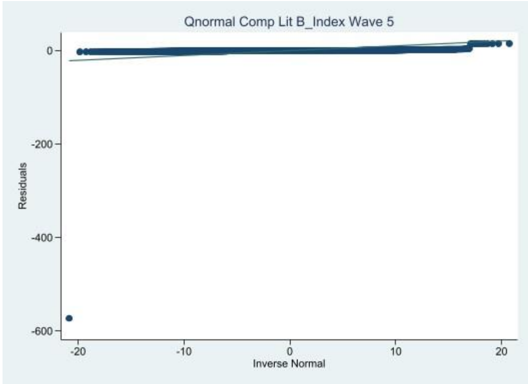


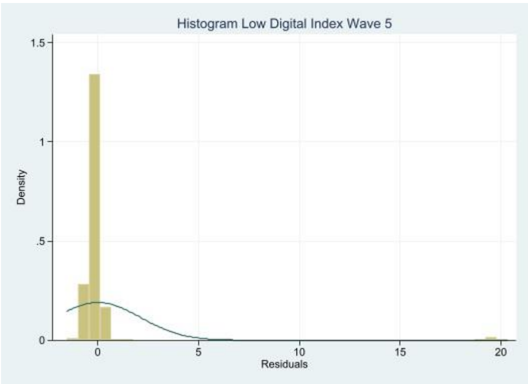


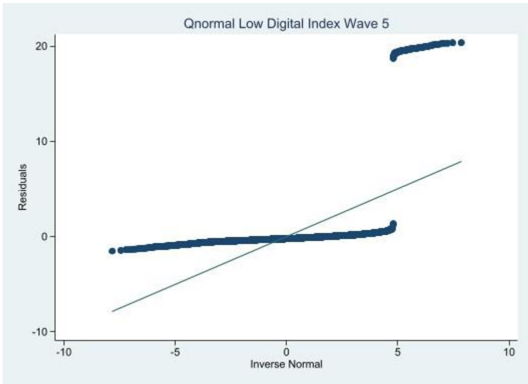





Qnormal Comp Lit Index Wave 5
Residuals
Inverse Normal
0
-100
-200
-300
-400
-20
-10
0
10
20


Qnormal Comp Lit B_Index Wave 5
Residuals
Inverse Normal
0
-200
-400
-600
-20
-10
0
10
20


Histogram Low Digital Index Wave 5
Density
Residuals
1.5
1
.5
0
0
5
10
15
20


Qnormal Low Digital Index Wave 5
Residuals
Inverse Normal
20
10
0
-10
-10
-5
0
5
10