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The relationship between digitalisation data and GDP

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A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business

Johannesburg, June 2023

ABSTRACT

This academic paper examines the relationship between digitalisation and Gross Domestic Product (GDP) in Sub-Saharan Africa (SSA). The study aimed to address the limited understanding of the impact of digitalisation on the economic growth and development of SSA countries. Existing literature, as explored in the background, underscores the positive impact of digitalisation on economic growth, particularly emphasizing the role of Information Communications Technology (ICT) (Solomon & Klyton, 2020; Paul, 2021). However, a noticeable gap persists, as there is limited empirical research investigating the specific relationship between digitalisation and GDP in the context of SSA.

By employing a quantitative research methodology, the study investigates the relationships between Internet usage, mobile phone usage, manufacturing value add, and GDP. The analysis utilises time series data from 1998 to 2020, obtained from the World Bank database, covering 10 countries, and resulting in 220 time series data points. It employed several statistical techniques such as time series regression, ARIMA, VAR, and exponential smoothing. It also used correlation and trend analysis, Pooled OLS, and cluster analysis to try and further understand the relationship.

The results show that in Sub-Saharan African (SSA) countries, there are slight positive connections between Internet usage, mobile phone usage, and GDP. Yet, it's important to note that the study recognizes limitations related to available data and time constraints, as highlighted in the literature (Tong & Wohlmuth, 2019). This emphasizes the necessity for more research to confirm and reproduce these findings. Moreover, a robust positive link is found between manufacturing value addition and GDP. Interestingly, when manufacturing value addition is considered as a control factor, the link between digitalisation and GDP becomes less strong. This implies that a portion of the positive impact of digitalisation on GDP is linked to the increased value addition in manufacturing.

The study contributes to existing literature by providing insights into the relationships between digitalisation and GDP in SSA while controlling for Manufacturing value Add. It emphasizes the importance of considering country-specific factors and contextual nuances in future research. Policymakers are recommended to focus on promoting investment in the manufacturing sector, increasing access to mobile phones and the internet, fostering innovation and entrepreneurship, investing in digital infrastructure, providing digital skills training, and fostering public-private partnerships to promote sustainable economic development in SSA.

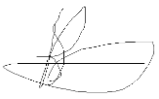
Further research is needed to validate these findings, explore the mechanisms through which Internet and mobile phone usage impact GDP, and understand the role of manufacturing value Add in driving economic growth. This deeper understanding will enable policymakers to make informed decisions to foster digitalisation, enhance mobile phone usage, and promote manufacturing value add for sustainable economic development in SSA and other developing African nations.

KEYWORDS

Digitalisation, GDP, Internet Usage, Manufacturing Value Add, Mobile Cellular Subscriptions

DECLARATION

I, BRIGHT SIKAZWE, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: BRIGHT SIKAZWE Signature: 

Signed at NORTHRIDIGING, JOHANNESBUERG

On the 30 June 2023

DEDICATION

With a heavy heart, I dedicate this research to my dear grandparents who passed away due to the coronavirus within just one week. Although they are no longer here with us, they will always have a special place in my heart. I offer this dedication to honour their memory and pray that their souls rest in peace in heaven, surrounded by the Lord's grace.

ACKNOWLEDGEMENTS

I would like to express my sincere appreciation for the unwavering support and invaluable guidance offered by my supervisor, Dr. Tebogo Sethibe. Additionally, I am deeply grateful to my family, friends, and colleagues for their selfless support and understanding, particularly during the most challenging moments. Finally, I extend my gratitude to the Almighty God for providing me with the strength and guidance necessary to navigate the difficulties posed by the COVID pandemic. I am immensely thankful for the contributions and support of each one of you, and I greatly value your presence in my life.

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LIST OF ACRONYMS

Abbreviation	Description
3IR	Third Industrial Revolution
4IR	Fourth Industrial Revolution
AME	Arab And Middle East
ARIMA	Auto regressio
DESI	Of Digital Economy and Society Index
DMA	Digital Maturity Assessment
DSDM	The Dynamic Spatial Durbin Model
FD	Financial Development
GDP	Gross Domestic Product
GMM	Fixed Effects (Fe)
GMM	Gaussian Mixture Models
ICT	Information Communications Technologies
IGTFP	Industrial Green Total Factor Productivity
IMF	International Monetary Fund
IoT	Internet of Things

NEDLAC	National Economic Development and Labour Council
OECD	Organisation For Economic Co-Operation and Development
OLS	Ordinary Least Squares
PLS	Employed Partial Least Squares
RPA	Robotic Process Automation
SADC	Southern African Development Community
SMS	Simple Message Service
SSA	Sub Saharan Africa
SVR	Support Vector Regression
UNDP	United Countries Development Programme
WEF	World Economic Forum

CHAPTER 1. INTRODUCTION

1.1 Statement of purpose

This study employs a quantitative methodology to examine the relationship between digitalisation and Gross Domestic Product (GDP) at the national level, with a specific focus on the Sub – Saharan Africa (SSA).

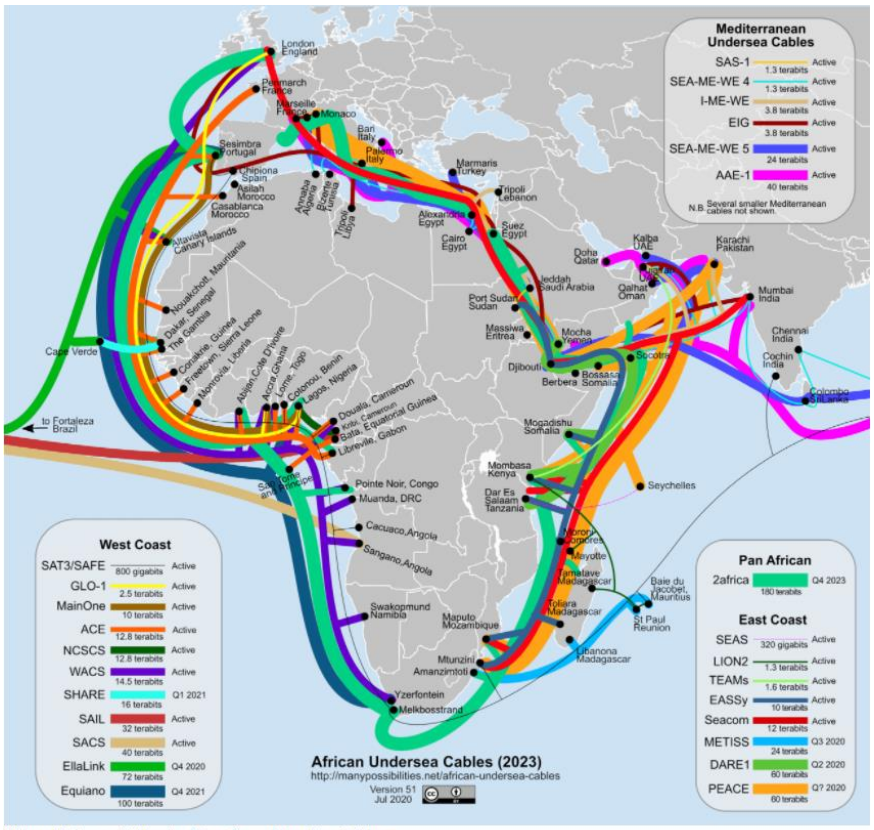
1.2 Background of the study

Digitalisation encompasses a wide range of communication equipment and applications, including radio, television, mobile phones, computers, network hardware, software, satellite systems, and associated applications (Kabongo & Okpara, 2014). A literature review by Solomon and Klyton (2020) indicates that digitalisation has a positive impact on economic growth, with a particular emphasis on the role of Information Communications Technology (ICT) in most studies. Paul (2021) further emphasizes the crucial role of the Internet in contemporary society, arguing that the adoption of digital technologies is increasingly essential.

Salahuddin and Gow (2016) acknowledge the growth in Internet usage over the past two decades and the resulting research into its economic implications. Elgin (2013) also highlights various economic impacts of the Internet, including technological advancements, increased investment, economic problem-solving, combating corruption, and promoting democracy.

Tong and Wohlmuth (2019) highlight the potential for digitalisation to have significant ramifications for economic growth. Solomon and Klyton (2020) concur, observing that many countries recognise the opportunities for economic growth offered by digital technologies. However, despite several governments implementing policies to increase Internet usage, Africa lags in this regard (Poushter, 2016). A report by the IFC (2022) estimates that 80% of individuals in Africa have limited or no access to the Internet, with affordability being a significant contributing factor. The report also emphasises the need to address underlying infrastructure challenges and prioritise the improvement of Internet infrastructure on the continent. Nevertheless, recent trends indicate a growth in Internet usage in Africa, driven primarily by the installation of high-speed underwater cables (Submarinenetworks.com, 2021), as shown in Figure 1.

Recent years have seen the African continent benefit from extensive undersea cables that provide Internet connectivity, as reported by submarinenetworks, and evidenced in Figure 1. Browne (2020) reports that Facebook is constructing a 37,000-kilometer undersea cable to enhance Internet connectivity in Africa, connecting 23 African, Middle Eastern, and European countries. It can therefore be argued that the responsibility for developing necessary inland infrastructure and providing the population with requisite consumer electronics falls to the individual governments of African countries and the policy measures they implement.



African Undersea Cables, by Steve Song, Many Possibilities

Figure 1 African Undersea cables (Source: Submarinenetworks.com)

Luis et al (2021) also conducted a study on economic development in Sub-Saharan Africa over the past fifty years and the concept of "Africa-rising." The study argued that further research is necessary to determine the sustainability of development observed in the past 15 years, given the breadth of the Africa-rising narrative. To this end, the authors proposed examining the time-series features of GDP in African countries. They emphasised that digital technology's impact on a country's GDP implies that adequately prepared countries will benefit their populations, highlighting the need for governments to adopt measures to prepare accordingly.

Thus, it can be argued that the significance of researching the relationship between GDP and digitalisation in African countries stems from the potential for digitalisation to promote economic growth and development in the region. The

African continent currently faces several economic challenges, including high levels of poverty, unemployment, and inequality (United Nations, 2019). Digitalisation can address these challenges by increasing productivity, fostering innovation, and creating new business models and opportunities (McKinsey Global Institute, 2016; Organisation for Economic Co-operation and Development, 2018).

However, the lack of research on the relationship between GDP and digitalisation in African countries (European Commission, 2019) limits the ability of policy makers and businesses to make informed decisions on leveraging digital technologies to drive economic growth and development in the region. Moreover, the disparities between African countries in terms of infrastructure, regulations, and human capital make it challenging to generalise findings from one country to another. Hence, research examining the relationship between GDP and digitalisation in African countries is necessary in this context to gain a deeper understanding of the potential economic benefits of digitalisation and help inform digital policy.

1.3 Research problem

The research problem identified in this study is the limited understanding of the impact of digitalisation on the economic growth and development of sub-Saharan African countries. While there has been an increasing adoption of digital technologies on the continent, there is still a lack of empirical research examining the relationship between digitalisation and GDP. This gap in knowledge limits the ability of policymakers and businesses to effectively utilise digital technologies to drive economic growth and development on the continent. Thus, this study seeks to address this research problem by investigating the relationship between digitalisation data and GDP through a quantitative research methodology. By

doing so, this study aimed to provide insights and recommendations that can inform policy decisions and initiatives aimed at promoting economic growth and development on the continent.

1.4 Research objectives

This study examined the relationship between digitalisation and GDP in SSA using internet and mobile phone usage data as proxies for digitalisation. The following research objectives were addressed to investigate this relationship:

a. *To establish whether there is a relationship between Internet usage data and GDP in SSA*

b. *To establish whether there is a relationship between Mobile phone usage data and GDP in SSA.*

c. *To investigate the effect of manufacturing value, add as a control variable on the relationship between Digitalisation and GDP.*

1.5 Rationale

The rationale for investigating the relationship between digitalisation and GDP in SSA is two-fold. Firstly, although numerous studies have explored the impact of digital technologies on economic growth, most of these studies have employed qualitative methods (Solomon and Klyton, 2021). Therefore, it is imperative to conduct additional research, particularly using quantitative methods, to enhance

our understanding of the relationship between digitalisation and economic growth. Secondly, the economies of many African countries heavily rely on commodities such as diamonds, copper mining, coal and oils exports, which are currently facing challenges including falling commodity prices and declining reserves (World Bank, 2020). Investigating the relationship between GDP and digitalisation can provide valuable insights into how digitalisation can be leveraged to diversify these economies and create new growth opportunities.

The study also aimed to contribute to the existing body of international research by providing local quantitative findings on the relationship between digitalisation and GDP in SSA. The study also seeks to assist those in leadership positions in making informed decisions about digital investments by demonstrating the positive impact of digitalisation on GDP and thus the living conditions for citizens. The findings of this study are thus expected to contribute to the growing pool of knowledge on the economic benefits of digital technologies and inform policy and business decisions in SSA and other countries seeking to understand the potential of digitalisation.

1.6 Delimitations of the study

The scope of this study was limited to investigating the relationship between two distinct digital technologies, namely Internet usage and mobile usage, and their impact on SSA's GDP. The dependent variable in this study was GDP growth rate, while the independent variables were the number of Internet users' growth rate and mobile users' growth rate. The research also considered the influence of manufacturing value-add on the variables under investigation.

1.7 Definition of terms

Digital connectivity - is the ability to communicate and collaborate using digital networks, to participate in research and scholarship, and to access and use information and communication technologies (ICT) devices (such as computers and mobile phones) or the internet (Bagchi, 2005; Belden, 2004).

Digitalisation – “The rethinking and reconfiguration of processes and systems from analogue and physical centric forms to maximally digital centric forms” (Armstrong & Lee, 2021).

GDP – “is the total of all resident producers' gross value added, plus any product taxes, minus any subsidies not accounted for in the product's value. The currency utilised is the current value of the US dollar”. (Worldbank.org).

Internet Users – “Internet users are defined as people who have used the Internet in the last three months from an Internet enabled device” (Worldbank.org).

Mobile cellular subscriptions – “All subscriptions to a public mobile telephone service that utilises cellular technology; this includes post-paid and all prepaid accounts that have been active for the last three months” (Worldbank.org).

1.8 Assumptions

The present study employed a quantitative research design and relied solely on publicly available secondary data from World Bank databases. No qualitative or interview data was incorporated into the analysis. The investigation of the relationship between digitalisation and GDP was delimited to specific digital technologies, specifically Internet usage and mobile usage. While other factors, such as unemployment statistics, commercial activities, government services, and financial services, are recognised as essential in determining GDP, they were not included in the study's scope. This decision was made to maintain a focused and manageable scope while still providing valuable insights into the examined relationship.

Additionally, despite the wide range of domains covered by digital technologies, such as cloud computing, the Internet of Things, data usage, and streaming, this study elected to narrow its focus to Internet usage and mobile usage due to time constraints and data availability issues.

1.9 Chapter Outline

Chapter 1 of the report gave the background of the investigation, the motivation for carrying out the study, the scope of the study, what the study does not cover and the limitations of the study.

In Chapter 2, a literature review is done to find out what research other researchers have done on the topic of digital technologies and GDP. The influence of digitalisation on GDP and other economic growth effects are also placed in context. Various approaches employed in past research examining the relationship between digital technologies and GDP are also explored and their

outcomes analysed. At the end of the chapter, theoretical models and an analytical framework are then presented.

Chapter 3 outlines the research design and research instruments adopted, including the data-gathering methodology, sampling and rationale of the approach chosen as well as its appropriateness and limits. The reliability and quality of data collected are examined while considering the ethical implications of the study.

In Chapter 4, the results of the study are presented and described and not explained. This is done proposition by proposition and then a summary of the chapter is given.

In Chapter 5, the results of the study are discussed and explained within the context of the literature in the literature review section (Chap. 2).

In Chapter 6 which is the last chapter, conclusions and recommendations are given together with suggestions for future research.

CHAPTER 2. LITERATURE REVIEW AND ANALYTICAL FRAMEWORK

2.1 Introduction

In this chapter, a literature review is done to find out what research other studies have done on the topic of digital technologies and GDP. The review starts with the definition of the key variables and subsequently outlines various sections that examine existing studies on the relationship between GDP and the levels of Internet usage, mobile phone penetration, and broadband penetration. The chapter then presents theoretical models and an analytical framework to provide a comprehensive understanding of the relationship under investigation. Finally, the review is concluded by summarising the key propositions and findings.

2.2 Definition of topic

2.2.1 Digitalisation

The term 'digitalisation' has various definitions in the literature. The following are sone of the definitions:

- Armstrong and Lee (2021) defined it as "the rethinking and reconfiguration of processes and systems from analogue and physical-centric forms to digital-centric forms."

- Hanelt et al. (2020) and Vial (2019) defined it as the use of digital technologies to produce value in new ways that result in organisational change.

- Antikainen et al. (2018) viewed digitalisation as a combination of cyber physical, Fourth Industrial Revolution technologies, and new business models that have the potential to create significant new opportunities for sustainable industrial value creation.

- Digitalisation is a trend that requires businesses to transform their strategy, processes, knowledge, and socio-technical system by enhancing their digital capabilities (Alsufyani and Gill, 2022).

- Digitalisation refers to "the integration of digital technologies into everyday life and the economy, including communication, commerce, and social interaction" (van Dijk, 2012, p. 1).

- Digitalisation involves "the deployment of digital technologies to enhance the efficiency and effectiveness of government, business, and civil society" (OECD, 2014, p. 10).

- Digitalisation is "the process of using digital technologies to improve the delivery of public services, enhance economic growth, and promote social inclusion" (European Commission, 2016, p. 4).

- Digitalisation refers to "the integration of digital technologies into all aspects of social and economic life, with the aim of improving productivity, innovation, and quality of life" (World Economic Forum, 2016, p. 5).

- Digitalisation is "the use of digital technologies to transform government, business, and society, including the creation of new products and services, new business models, and new forms of governance" (Kshetri, 2018, p. 195).

- Digitalisation involves "the digitization of data, the automation of processes, and the use of digital technologies to enhance collaboration and decision-making across organizations and sectors" (United Nations, 2019, p. 4).

- Digitalisation is "the application of digital technologies to create new business models, improve productivity and efficiency, and enhance customer experiences" (Bughin & Manyika, 2017, p. 2).

- Digitalisation refers to "the integration of digital technologies into all aspects of the economy, including production, distribution, and consumption, with the aim of increasing efficiency, reducing costs, and enhancing value creation" (Dutta et al., 2018, p. 6).

- Digitalisation involves "the use of digital technologies to create new opportunities for economic and social development, including the creation of new jobs and industries, the enhancement of public services, and the promotion of innovation and entrepreneurship" (UNCTAD, 2020, p. 5).

In this study, the definition of digitalisation was restricted to a narrower focus, specifically the part of technology component of the ecosystem i.e., a combination of Internet access data and mobile cellular subscriptions data.

2.2.2 GDP

Like the concept of digitalisation discussed earlier, the term ‘GDP’ has been defined in different ways by various scholars, as shown below.

- "GDP is defined by the World Bank as the gross value added in the economy by all resident producers, plus any product taxes and minus any subsidies not included in the product value" (Worldbank.org).

- "GDP is defined by Murat et al. (2021) as a monetary measure of all finished products and services produced within a country over a specified period”.

- "Bergh (2022) defined GDP as the monetary, market worth of all final products and services produced in a country over a year by both citizens and non-citizens”.

- According to Cai et al (2022), the Chinese government calculates GDP using three methods: the income method, the expenditure method, and the value-added method.

- Hao et al. (2022) stated that GDP is the most widely used and relevant indicator of overall economic activity and provides useful information to policymakers, investors, market participants, and businesses.

- "GDP growth (annual %) represents the annual percentage change in GDP and measures the rate at which the GDP is growing or shrinking. A positive value indicates economic growth, while a negative value indicates economic contraction".

- "GDP measures the market value of all final goods and services produced within a country in a given period of time." (Mankiw, 2020, p. 194)

- "GDP represents the total market value of all goods and services produced within a country's borders in a given time period, usually a year." (Taylor, Weerapana, & Tauchen, 2017, p. 158)

- "GDP is the monetary value of all final goods and services produced within a country's borders in a given period of time." (Abel, Bernanke, & Croushore, 2017, p. 281)

- "GDP measures the monetary value of all final goods and services produced within a country in a given period of time." (Blanchard, 2017, p. 158)
- Reference: Blanchard, O. (2017). Macroeconomics. Pearson Education.

- "GDP is the total value of goods and services produced within a country's borders in a given period of time, usually a year." (Miller, 2019, p. 146)

- "GDP is the monetary value of all final goods and services produced within a country's borders in a given time period." (Case, Fair, & Oster, 2019, p. 158)

- "GDP is the sum of all final goods and services produced within a country in a given period of time, usually a year." (Parkin, 2017, p. 179)

- "GDP is the market value of all final goods and services produced within a country in a given period of time." (Begg, Fischer, & Dornbusch, 2017, p. 294)

- "GDP is the monetary value of all final goods and services produced within a country's borders in a given period of time." (Krugman, Wells, & Graddy, 2019, p. 148)
- Publishers.

- "GDP measures the value of all final goods and services produced within a country in a given period of time." (McConnell, Brue, & Flynn, 2020, p. 216)

For this study, the definition of GDP that was adopted is as per the World Bank definition. Therefore, GDP is defined as "the total of all resident producers' gross value added, plus any product taxes, minus any subsidies not accounted for in the product's value. It is estimated without considering depreciation of produced assets or the depletion and deterioration of natural resources. The currency utilised is the current value of the US dollar" (Worldbank.org).

2.3 Internet Usage and GDP

As stated in the previous sections, “Internet users are defined as people who have used the Internet in the last three months from an Internet enabled device such as a mobile phone, tablet or laptop”. (Worldbank.org).

Salahuddin and Gow (2016) conducted a study in South Africa to investigate the impact of Internet usage, financial development, and trade openness on

economic growth. The study used the structural unit root test, as well as the Johansen and ARDL cointegration tests to analyse annual time series data from 1991 to 2013 World Development Indicators Database. The authors concluded that while Internet use in South Africa had grown and long-term relationships between the variables were found, the short-term impacts seemed insignificant. The findings make sense given the long-term nature of economic growth. While the Internet can immediately enhance people's lives on an individual level, it takes an entrepreneurial ecosystem to use the Internet innovatively to observe growth benefits on a national level (Worldbank.org).

Clarke et al. (2015) used regression techniques to investigate the relationship between Internet access and growth and productivity of companies. The authors concluded that when companies have more Internet access, they have more growth and productivity. They further claimed that the findings are consistent regardless of the size of the company or the amount of technology used, and that small businesses benefit more from the Internet than bigger organisations. In line with Clarke et al. (2015), it can be further argued that while large corporations are hampered by systems and processes, small businesses can be more agile and creative in their application of the Internet's benefits. A small business can opt to migrate all of its resources to the cloud in a short period of time, whereas larger businesses would take longer. However, as the authors have shown, the Internet provides both short and long-term benefits for all organisations.

Harb (2017) used the enhanced Solow model, cast into a dynamic panel data environment, to investigate the influence of the Internet penetration rate and the investment in the communications industry (as a proportion of GDP) on economic growth in the Arab and Middle East (AME) countries. The author evaluated the regressions using the SGMM estimation approach. The study found evidence that the Internet plays a key role in high-income AME countries but not in low-income countries. Oddly, they also found evidence that telecom investments did not affect economic growth in the region. This finding on telecom investments is

particularly surprising given that most Internet usage occurs on mobile phones, and the study was conducted in 2017 in highly developed countries with strong mobile penetration. However, it's possible that this is the case since many countries already have telecom infrastructure in place, making additional investments of little or no value in the economy growth prospects of these countries.

Fernández-Portillo et al (2020) suggested that the advancement in the deployment and usage of ICT promotes the economic growth of countries that can be classified as developed European economies. The authors concluded that the number of Internet users is the greatest performance indicator, followed by reading of news and social networks. They employed Partial Least Squares (PLS) and utilised Digital Economy and Society Index (DESI) datasets to study European Economic Community countries, that are members of the OECD. According to these findings, it may be argued that the number of Internet users is the most significant factor because most business is now done online. Similarly, the finding regarding news consumption may indicate that these economies are advanced because news affects stock markets. Social media platforms are also being used as a commercial platform in recent years. Lessons for African nations include the fact that the economy benefits from investments in telecom infrastructure, particularly as the number of Internet users grows.

Katz et al (2020) studied the impact of digitisation on the 2003 SARS outbreak by utilising the Cobb-Douglas production function and ordinary least squares (OLS) estimation methods. The results of the study showed that nations that had a well-established broadband infrastructure were more capable of mitigating the economic consequences of the pandemic. The authors highlight the significance of these findings, and the need to apply the lessons learned in future pandemics, such as the ongoing COVID-19 crisis, which had led to widespread restrictions and economic decline.

Watanabe et al (2018) evaluated the co-evolution of Internet progress, increased reliance on uncaptured GDP, and a shift in people's preferences. This was based on their theory that people's preferences extend beyond economic value. They used a method of trending the data over time and found that, while the Internet had resulted in more services and benefits for people, productivity in developed countries appears to have slowed. As a result, they began to question the validity of GDP estimates to determine economic value. However, it might be claimed that Watanabe et al. (2018) only considered industrial productivity and did not compare their patterns to determine whether the digital economy had expanded during the same period. Their conclusion regarding how GDP is calculated is significant because it emphasises the necessity of including the digital economy in the computation to account for unreported GDP.

Zhang (2021) proposed an economic model based on the Cobb-Douglas production function to explain why broadband played such a significant role in economic growth in China during the COVID-19 outbreak. The findings revealed that the technology enhanced human capital throughout the epidemic and supported the country's economic recovery in the first few months.

Yu (2022) examined how the Internet's growth affects the green economy at an industrial scale using the Dynamic Spatial Durbin Model (DSDM) and Chinese panel data. The growth of the Internet, according to them, has aided the development of the industrial green economy. They go on to argue that this is because the Internet may aid in the expansion of industrial structures by making innovation more accessible.

Based on the studies you provided, it can be concluded that the growth of the Internet has a significant impact on economic growth and development. The

studies suggest that countries with well-established broadband infrastructure are more capable of mitigating the economic consequences of pandemics such as COVID-19. The Internet has also aided the development of the industrial green economy by making innovation more accessible. However, there are concerns about the validity of GDP estimates to determine economic value and the need to include the digital economy in the computation to account for unreported GDP. Table 1gives a summary of all the prior studies

2.3.1 Proposition

The literature reviewed showed that there is a correlation between Internet Usage and an uplift in economic growth (GDP).

Table 1 . Summary of prior studies on the relationship between GDP and Internet Usage

Author(s)	Topic dealt with	Methods used	Finding
Salahuddin and Gow (2016)	To investigate the impact of Internet usage, financial development, and trade openness on economic growth	Structural unit root test, as well as the Johansen and ARDL cointegration tests	Internet use in South Africa had grown and found long term relationships between the variables, but the short-term impacts seemed insignificant.
Clarke et al. (2015)	To show that the Internet may be used for a variety of purposes	Regression techniques	when companies have more Internet access, they have more growth and productivity.
Harb (2017)	To examine the influence of the Internet penetration rate and the investment in the communications industry (as a proportion of GDP) on economic growth in the Arab and Middle East (AME) countries.	Solow model, cast into a dynamic panel data environment. Evaluated regressions using the SGMM estimation approach	Found evidence that the Internet plays a key role in high income AME countries but not in low-income countries.

Fernández-Portillo et al (2020)	The advancement in the deployment and usage of ICT promotes the economic growth of countries that can be classified as developed European economies.	Partial Least Squares (PLS)	Concluded that the number of Internet users is the greatest performance indicator, followed by reading of news and social networks.
Katz et al (2020)	The impact of digitisation on the 2003 SARS outbreak	Cobb-Douglas production function and ordinary least squares (OLS) estimation methods	The results of the study showed that nations that had a well-established broadband infrastructure were more capable of mitigating the economic consequences of the pandemic.
Watanabe et al (2018)	Co-evolution of Internet progress, increased reliance on uncaptured GDP, and a shift in people's preferences.	Method of trending the data over time	, while the Internet had resulted in more services and benefits for people, productivity in developed countries appears to have slowed.
Zhang (2021)	To explain why broadband played such a significant role in economic growth in China during the COVID-19 outbreak	Cobb-Douglas production function	Technology enhanced human capital throughout the epidemic and supported the country's economic recovery in the first few months.

Yu (2022)	How the Internet's growth affects the green economy at an industrial scale	Dynamic Spatial Durbin Model (DSDM	The growth of the Internet has aided the development of the industrial green economy.

2.4 Mobile phone penetration and GDP

Mobile phone penetration or mobile cellular subscriptions (per 100 people) can be defined as services including private trunked mobile radio, telepoint, radio paging, and telemetry (Worldbank.org).

Miyajima (2022) conducted a study to investigate the relationship between mobile phone ownership and food consumption in South Africa. The study utilised data obtained from household surveys and employed three distinct regression techniques, namely pooled ordinary least squares (OLS), panel fixed effects, and system GMM. The findings revealed a positive association between mobile phone ownership and food consumption. Specifically, mobile phone owners consumed 10-20% more than those without mobile phones. However, the study stated that individuals with lower food consumption benefit more from mobile phone ownership. This observation could be attributed to the tendency of individuals with lower food consumption to save more money for other expenses.

Fosu (2011) argued that Ghana's outdated fixed-line infrastructure poses an obstacle to achieving universal Internet access in the country. As a possible solution, the author recommends the adoption of wireless technology. However, the author also acknowledges that high entry fees present a barrier to the wider deployment of wireless broadband in Ghana. This observation may have implications for other countries in the African region with similar GDP levels to Ghana, as the deployment of wireless technology is often considered to be more feasible than upgrading existing infrastructure.

Hasbi and Dubus (2020) conducted a study to investigate the factors that influence mobile broadband use in developing economies using discrete choice models. They found evidence that owning a SIM card and belonging to an online social community has a strong positive impact on mobile broadband usage. The study also found that different countries utilise mobile broadband differently, with some countries showing higher usage among the unemployed, while others showing higher usage among students. However, the study suggests that overall, mobile broadband can help to raise people's living standards. The researchers also noted that different countries in Africa have unique circumstances, and more research is needed to compare these relationships across different regions.

Kongaut and Bohlin (2016) used OLS to estimate mobile broadband adoption and usage in Sweden. They concluded that because of the cheaper costs, lower-income consumers tend to utilise it more for daily tasks, and governments should use these findings to enhance infrastructure investments because high broadband adoption can help close the digital divide. Even though this research was conducted in a developed country, the findings show that there are some lessons to be learned by African countries.

Myovella et al (2020) examined the contribution of digitalisation to the economic growth of Sub-Saharan Africa (SSA) in comparison with the OECD economies using GMM estimators. They found evidence that while broadband Internet and mobile telecommunications have different effects in OECD and SSA countries, digitalisation overall has a positive impact on economic growth for both groups of countries.

Donou-Adonsou (2019) investigated if education influences the relationship between economic development and technological development in Sub- Saharan Africa (SSA) using a GMM estimator. The study provides evidence that for countries with a more highly educated population, the Internet is a driver for

growth while mobile phone usage was found to be less of a driver. They also concluded that while education is crucial for Internet usage it was not a major factor in mobile phone usage. This conclusion can also lead to an argument that there is then a need for governments in African countries to invest in digital technologies which also tend to lower the cost of education because the Internet comes with a lot of free educational resources.

Kanyam et al. (2017) conducted a study utilising Granger causality test to examine the influence of mobile phone penetration, Internet usage, and the interplay between the two on corruption in Sub-Saharan Africa (SSA). The findings indicated that mobile phones could serve as a valuable tool in the fight against corruption, which negatively impacts economic growth and living standards. The authors note that individuals with access to mobile phones have the ability to report instances of corruption through hotlines and can also play a role in deterring voter fraud by promptly reporting such incidents. These actions, in turn, have a direct effect on economic growth. Based on these conclusions, it can be argued that the widespread adoption and use of mobile phones has the potential to enhance living standards by reducing corruption and promoting fair elections.

Kim et al. (2021) conducted a study to examine the impact of Information and Communication Technology (ICT) investment on productivity at the country-level. The study employed both pooled OLS regression models and fixed-effect regression models using the Cobb-Douglas production function. To control for aggregate time series trends, the regression models also incorporated year fixed effects based on panel data. The results indicated that the investment in mobile ICT has a significant effect on boosting economic growth in developing countries, but there was no empirical evidence of such influence in developed or undeveloped countries.

It can be concluded that digitalisation has a positive impact on economic growth in both developed and developing countries. Mobile broadband adoption and usage can help close the digital divide and enhance living standards by reducing corruption and promoting fair elections. Education is crucial for Internet usage but not a major factor in mobile phone usage. Investment in mobile ICT has a significant effect on boosting economic growth in developing countries. Governments should invest in digital technologies which also tend to lower the cost of education because the Internet comes with a lot of free educational resources. Table 2 is a summary of all the prior studies described in this section.

2.4.1 *Proposition*

The literature reviewed showed that there is a correlation between Mobile Phones penetration and usage and an uplift in economic growth (GDP).

Table 2 Summary of prior studies on the relationship between GDP and mobile Usage

Author(s)	Topic dealt with	Methods used	Finding
Miyajima (2022)	The relationship between mobile phone ownership and food consumption in South Africa	Pooled ordinary least squares (OLS), panel fixed effects, and system GMM	The findings revealed a positive association between mobile phone ownership and food consumption
Fosu (2011)	The limitations posed by Ghana's outdated fixed-line infrastructure pose an obstacle to achieving universal Internet access in the country.	Thematic analysis	recommends the adoption of wireless technology.
Hasbi and Dubus (2020)	The factors that influence mobile broadband use in developing economies	Discrete choice models	Found evidence that owning a SIM card and belonging to an online social community has a strong positive impact on mobile broadband usage.
Kongaut and Bohlin (2016)	For their estimates on mobile broadband adoption and usage in Sweden	OLS	Concluded that because of the cheaper costs, lower-income consumers tend to utilise it more for daily tasks, and governments should use these findings to enhance

			infrastructure investments because high broadband adoption can help close the digital divide.
Myovella *et al* (2020),	The contribution of digitalisation to the economic growth of Sub-Saharan Africa (SSA) in comparison with the OECD economies.	GMM estimators,	Found evidence that while broadband Internet and mobile telecommunications have different effects in OECD and SSA countries, digitalisation overall has a positive impact on economic growth for both groups of countries.
Donou-Adonsou (2019)	Investigates if education influences the relationship between economic development and technological development in Sub- Saharan Africa (SSA)	GMM estimator	Provides evidence that for countries with a more highly educated population, the Internet is a driver for growth while mobile phone usage was found to be less of a driver.
Kanyam et al. (2017)	the influence of mobile phone penetration, Internet usage, and the interplay between the two on corruption in Sub-Saharan Africa (SSA).	Granger causality	The findings indicated that mobile phones could serve as a valuable tool in the fight against corruption, which negatively impacts economic growth and living standards.

Kim et al. (2021)	The impact of Information and Communication Technology (ICT) investment on productivity at the country-level.	Pooled OLS regression models and fixed-effect regression models using the Cobb-Douglas production function.	The results indicated that the investment in mobile ICT has a significant effect on boosting economic growth in developing countries, but there was no empirical evidence of such influence in developed or undeveloped countries.

2.5 Manufacturing Value Add and GDP as a Control Variable

The use of a manufacturing value-added control variable to explore the relationship between GDP and digitalisation (e.g., mobile users, internet users) is crucial because it can provide insight into the causal relationship between the two. For instance, previous academic articles have suggested that there is a positive correlation between GDP and the number of mobile and internet users. However, this relationship is likely to be driven by a third factor such as the increase of manufacturing value-added. By controlling for this factor, it is possible to examine the direct effect of digitalisation on GDP. Several studies have investigated this relationship as outlined in the following paragraphs.

Hosseinzadeh (2018) conducted a study to examine the relationship between manufacturing value-added and GDP in both developed and developing countries. The results of the study suggest that the contribution of manufacturing value-added to GDP is higher in developed countries than in developing countries and that the relationship between the two variables is strong and positive. Furthermore, the author found that the contribution of manufacturing value-added to GDP is higher in countries with higher levels of human capital, openness to trade, and financial development. These results suggest that policies aimed at improving the level of human capital and openness to trade, as well as supporting financial development, could lead to increased economic growth.

Wang (2016) conducted a study to investigate the relationship between financial development and economic growth, with a particular focus on the role of manufacturing value-added. The article found that financial development has a strong positive effect on economic growth, and that this effect is strengthened when manufacturing value-added is considered. The article also found that the effect of financial development on economic growth is greater in countries with

relatively low levels of manufacturing value-added. This suggests that manufacturing value-added plays an important role in the relationship between financial development and economic growth.

Salim (2015) conducted a study to examine the impact of manufacturing value-added on economic growth in the USA. The study found that manufacturing value-added has a positive and significant effect on economic growth, and that this effect is stronger in states with a higher percentage of manufacturing activity. Additionally, the article found that the impact of manufacturing value-added on economic growth is nonlinear, with a higher contribution when the manufacturing sector is relatively large. The study also found that the impact of manufacturing value-added is strongest in states that are more heavily reliant on the manufacturing sector.

Singh (2013) explored the role of manufacturing value-added in India’s economic growth. The study used a sample of 325 Indian firms and found that manufacturing value-added has a positive and significant effect on economic growth. The article also found that the effect of manufacturing value-added is stronger in states with a higher percentage of manufacturing activity, and that the impact of manufacturing value-added is strongest in states that are more heavily reliant on the manufacturing sector. The article concluded that manufacturing value-added has an important role to play in India’s economic growth.

According to Kumar and Kumar (2010), who examined the role of manufacturing value-added in India's economic growth. The study used a sample of 814 Indian firms and found that manufacturing value-added has a positive and significant effect on economic growth. The article also found that the effect of manufacturing value-added is stronger in states with a higher percentage of manufacturing activity, and that the impact of manufacturing value-added is strongest in states that are more heavily reliant on the manufacturing sector. Additionally, the article

found that the effect of manufacturing value-added is stronger in states with a higher level of economic development. The article concluded that manufacturing value-added has an important role to play in India's economic growth. Table 3 is a summary of all the prior studies described in this section.

2.5.1 *Proposition*

The literature reviewed showed that using manufacturing value-added control variable can provide insight into the causal relationship between GDP and digitalisation.

Table 3 Summary of prior studies on the relationship between GDP and manufacturing value add.

Author(s)	Topic dealt with	Methods used	Finding
Hosseinzadeh (2018)	The relationship between manufacturing value-added and GDP in both developed and developing countries.	Panel data analysis method	The study found that manufacturing value-added has a positive and significant effect on GDP in both developed and developing countries.
Wang (2016)	The relationship between financial development and economic growth, with a particular focus on the role of manufacturing value-added.	Panel data analysis method	The study found that manufacturing value-added has a positive and significant effect on the relationship between financial development and economic growth1.
Salim (2015)	The impact of manufacturing value-added on economic growth in the USA	Panel data regression model	The study found that manufacturing value-added has a positive and significant effect on economic growth, and that this effect is stronger in states with a higher percentage of manufacturing activity.
Singh (2013)	The role of manufacturing value-added in India's economic growth	Econometric tests are performed based on a panel data	Manufacturing value-added has a positive and significant effect on economic growth

Kumar and Kumar (2010),	The role of manufacturing value-added in India's economic growth.	Narrative literature review of 112 papers	The effect of manufacturing value-added is stronger in states with a higher percentage of manufacturing activity, and that the impact of manufacturing value-added is strongest in states that are more heavily reliant on the manufacturing sector.

2.6 ANALYTICAL FRAMEWORK

This section delves into the theoretical foundations that underpinned this study, including the guiding principles and concepts that guided the research. Additionally, a conceptual framework is presented, highlighting the specific variables and their interrelationships that the study aimed to examine.

2.6.1 *Theoretical Frameworks*

The theoretical models that were relevant to this study include the Neoclassical models, specifically the Solow-Swan growth model, which refers to industrial technology and the digital economy model which has a greater emphasis on digital technologies in comparison to industrial technology.

a. *Solow-Swan Neoclassical model*

In accordance with the Neoclassical growth model, capital accumulation in an economy and its utilisation by individuals are pivotal determinants of economic growth. The interplay between capital and labour determines the economy's total output. Furthermore, technology is viewed as a key factor that drives labour productivity, leading to increased total production through improved labour efficiency. The Neoclassical growth model's production function is used to assess an economy's economic growth and stability. (''Theories of Growth'', 2022)

The general production function in the neoclassical growth model takes the following form:

$$Y = A*F(K, L)$$

Where:

Y is the GDP

K is the amount of capital in the economy

L is the amount of unskilled labour in the economy

A represents the level of technology

This production function asserts that technology augments labour and that worker productivity is proportional to the level of technology. It also shows how GDP is a function of capital, labour, and technology.

As argued in the previous section, the Solow-Swan Growth model is a prominent version of the Neoclassical growth theory that models the relationship between economic growth and three critical factors: labour, capital, and technology. It is according to Solow and Swan (1956), widely considered as the simplest and most prevalent model of this theory. The model posits that a consistent growth rate is achieved when these three forces are in equilibrium.

To this effect, numerous studies have relied on the Solow-Swan Growth model in the analysis of GDP growth. For instance, Dohtani (2010) constructed an endogenous Solow-Swan growth cycle model and found that high economic growth rates are inconsistent with economic stability. This finding supports the

notion that the Solow-Swan growth model is a valuable tool for evaluating the relationship between growth and other economic variables.

Mungua et al. (2019) presented a new approach for estimating the Solow-Cobb-Douglas economic growth model and uncovered new insights into its performance when applied to economic data. This indicates that researchers continue to explore ways to improve and refine the Solow-Swan Growth Model, underscoring its ongoing relevance in economic research, especially in the examination of GDP growth.

Zhang et al. (2021) evaluated the "Solow paradox" in the context of China and concluded that trade liberalisation is essential for developing countries to overcome this phenomenon. The Solow paradox refers to the observation that despite significant investments in physical capital, many countries do not experience correspondingly high economic growth rates. The authors' conclusion highlights the continued relevance of the Solow-Swan Growth Model in economic research and its connection to trade policies.

Durusu-Ciftci et al. (2017) developed a Solow-Swan growth model that considers financial markets and discovered that credit markets and equity from stock markets are two long-term predictors of GDP per capita. This study provided evidence of the crucial role of financial markets in economic growth and highlighted the continued relevance of the Solow-Swan Growth Model in research on this subject.

In conclusion, the Solow-Swan Growth Model is a widely accepted and simple model within the Neoclassical Growth theory that describes the relationship between economic growth and three key factors: labour, capital, and technology. The model has been used to analyse the relationship between growth and other

economic factors and is continually being improved and refined by researchers. The Neoclassical Growth model emphasises the importance of capital, labour, and technology in determining economic growth and highlights the connection between trade policies and economic growth.

b. *Digital economy model*

The digital economy is a complex concept involving economic activities changed by digital technologies (OECD, 2023). It goes beyond traditional activities, connecting people, businesses, devices, and data through the internet and technology (Deloitte Malta, 2023). This hyperconnectivity, driven by the internet, mobile tech, and IoT, forms the core of the digital economy (Western Cape Government, 2023).

Various definitions highlight the digital transformation of economic activities. According to TechTarget (2023), it refers to activities emerging from connecting individuals, businesses, devices, data, and operations through digital technology. This sets it apart from the traditional economy, relying on online transactions and disrupting established industries (TechTarget, 2023). While the digital economy offers growth opportunities, it also brings challenges like digital divides, cybersecurity threats, and ethical concerns about data privacy (OECD, 2023).

The digital economy model refers to economic activity resulting from widespread use of digital technologies like the Internet, mobile devices, and digital platforms. This connection between the digital economy and GDP has been a subject of research and debate. McKinsey Global Institute (2016) suggests the digital economy could add $2.2 trillion to $2.6 trillion to global GDP by 2025. The World Bank (2018) finds a 10% increase in high-speed Internet penetration can increase GDP per capita in developing countries by 1.3%. OECD (2016) notes a positive

impact on GDP growth but highlights complexities influenced by factors like digital infrastructure and skills. Boston Consulting Group (2019) adds that while the digital economy is linked to GDP growth, the relationship is moderated by a country's development level and innovation.

In conclusion, the link between the digital economy and GDP is complex, influenced by factors like digital infrastructure, skills, regulatory environment, and the country's development and innovation levels.

c. *Combination of Solow-Swan and Digital Economy models*

In this study, the relationship between GDP and digitalisation in SSA was explored by drawing upon two theoretical models: the Solow-Swan and Digital Economy models. Firstly, the variables to be measured were defined. In this case, Internet Users, and Mobile Users were chosen as the independent variables, with GDP as the dependent variable. Then, an empirical analysis was conducted to examine the relationship between digitalisation and GDP in SSA.

The Digital Economy model was then utilised to analyse the impact of digitalisation on GDP in SSA. As mentioned earlier, this model states that the widespread adoption of digital technologies can lead to substantial economic growth and a corresponding increase in GDP. On the other hand, the Solow-Swan model was used to analyse the impact of investment in digital infrastructure and human capital which in this case was the manufacturing value add which also acted as a control variable.

The combined framework of these two models provided a comprehensive and systematic approach to understand the relationship between digitalisation and GDP in SSA. This framework could also serve as a basis for further research and policy formulation in this area.

2.6.2 *Conceptual Framework*

A conceptual model has been proposed based on the theoretical models mentioned earlier, depicted in Figure 2. This study concentrates on understanding how digital technologies impact Gross Domestic Product (GDP), considering GDP as a multifaceted phenomenon influenced by various factors. The conceptual framework integrates the Digital Economy Model and the Neoclassical Solow-Swan Growth Model to assess the correlation between digitalization and GDP. The independent variables include the number of internet users, representing accessibility to digital technologies, and the number of mobile users, indicating the level of mobile device access and usage. The dependent variable is GDP, reflecting overall economic growth. Additionally, the study introduces a control variable: manufacturing value.

The Neoclassical Solow-Swan Growth Model helps in comprehending connections between economic growth, capital accumulation, and technological progress. Simultaneously, the Digital Economy Model provides insights into how digital technologies, especially the Internet and mobile devices, influence economic activities.

In the upcoming discussion section, this conceptual framework will be systematically applied to explore the relationships between these variables. It serves as a guiding tool, ensuring a structured analysis and a thorough understanding of the intricate interactions examined in this study.

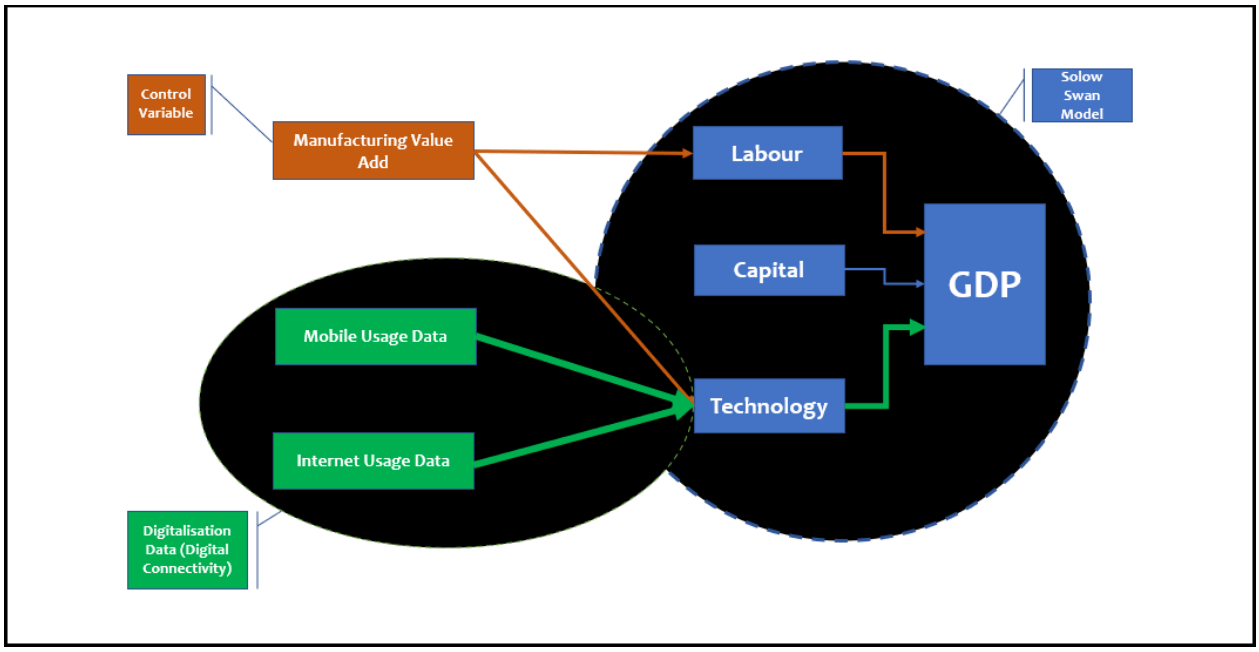


Figure 2 Conceptual Framework (Solow Swan + Digital economy)

In conclusion, the conceptual framework is a crucial instrument for interpreting findings within the context of the Neoclassical Solow-Swan Growth Model and the Digital Economy Model. It suggests that the level of digitisation in an economy, measured by internet and mobile users, positively influences GDP. However, this relationship depends on a country's development level and degree of innovation, supported by Boston Consulting Group (2019). The model incorporates manufacturing value add as a control variable to consider its contribution to economic growth.

2.7 Conclusion of Literature Review

In conclusion, it can be inferred that internet usage and mobile phone penetration have a positive impact on economic growth, business productivity, food

consumption and internet access in the long term. Additionally, using a manufacturing value-added control variable can provide insight into the causal relationship between GDP and digitisation. The literature also shows that the contribution of manufacturing value-added to GDP is higher in developed countries than in developing countries and the relationship between the two variables is strong and positive.

Regarding theoretical models, it can be concluded that the literature indicates that the Solow-Swan Growth model remains a relevant and widely used tool in economic research, specifically in the analysis of GDP growth. Researchers continue to build upon and improve the model to better understand the dynamics of economic growth. Additionally, recent advancements in growth models, such as the digital economy model have emerged and suggest that the digital economy has the potential to significantly impact economic growth and GDP. However, it is important to note that the relationship between the digital economy and GDP growth is multifaceted and is influenced by various factors such as investment in digital infrastructure, digital skills, and the regulatory environment.

A conceptual framework combining the digital economy model and the Solow-Swan growth model was developed to measure the relationship between digitisation and GDP. The framework proposes that digitisation has a positive impact on GDP, but this relationship is influenced by the level of development and innovation. The control variable, manufacturing value add, was included in the model to account for its contribution to the economy.

The propositions for the study are as restated below:

1. The literature reviewed shows that there is a correlation between Internet Usage and an uplift in economic growth (GDP).

2. The literature reviewed shows that there is a correlation between Mobile Phones penetration and usage and an uplift in economic growth (GDP).

3. The literature reviewed shows that using manufacturing value-added control variable can provide insight into the causal relationship between GDP and digitisation.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

The previous chapter reviewed the literature on the relationship between digitalisation technologies and GDP. This chapter discusses the research paradigm used to conduct this study and describes the target population. Additionally, this chapter outlines the sampling methodology and time frame, data collection techniques, and considerations regarding reliability and validity. It also examines ethical considerations, research limitations, and statistical methods used for data analysis.

3.2 Research Design

The research design employed in this study is well-suited for addressing the research questions and objectives. The utilisation of quantitative research methods facilitates the systematic analysis of data and the identification of statistical relationships between variables. The use of data spanning from 1998 to 2020, derived from a sample of 10 countries, resulting in 220 time series data points, is appropriate for conducting statistical analysis and examining trends and changes in digital connectivity adoption over time. Various statistical methods, including trend analysis, time series regression analysis (VAR & Pooled OLS), and additional tests such as correlation analysis and cointegration tests for long-term effects, were employed to enable a comprehensive analysis of the relationship between digitalisation and GDP in SSA.

The use of data from the World Bank database is appropriate as it is a reputable source that provides reliable and comparable data across countries. The inclusion of a control variable, manufacturing value add, in the time series regression models is also appropriate for accounting for its contribution to the economy and its potential influence on the relationship between digitalisation and GDP. All variables were transformed into growth rates to achieve stationarity of the data, which is a prerequisite condition for time series analysis.

Overall, the research design is robust and provides a rigorous approach to examining the relationship between digitalisation and GDP in SSA, though it does have some limitations which will be highlighted in subsequent sections.

3.3 Units of Analysis

In this study, digital connectivity adoption was represented by mobile and internet users and used as a proxy for digitalisation. GDP was used as a proxy for economic growth. Armstrong and Lee (2021) identified four major technologies that drive digitalisation: Internet access, computer networks, data storage and analysis, and mobile technologies. Based on the digital economy and slow-swan models that serve as the theoretical foundation of this study, it was deemed appropriate to use Internet users and mobile cellular subscriptions as proxies for digitalisation due to data availability and time constraints.

GDP was considered a good proxy for economic growth because it tracks changes in the size of an entire economy. In addition to serving as a comprehensive measure of economic health, GDP reports provide insights into factors driving economic growth or holding it back (Investopedia, n.d.).

Manufacturing value add was included as a control variable in this study to isolate the effect of digitalisation on economic growth from other potential drivers such as manufacturing activities. Manufacturing is a crucial sector of the economy and digital technologies have been shown to improve its productivity and efficiency leading to higher value-added activities. By controlling for manufacturing value add, it was ensured that any observed relationship between digitalisation and economic growth is not solely due to indirect effects on GDP.

3.4 Population

The selection of the primary population for this study focused on all African countries within sub-Saharan Africa. The decision to narrow down the sample to specific countries, namely, Angola, Botswana, South Africa, Namibia, Zambia, Nigeria, Kenya, Mozambique, Uganda, and Rwanda, was driven by the desire to capture a representative cross-section of the sub-Saharan African region. This subset of countries was carefully chosen based on considerations of their diverse levels of economic development, distinct stages of digitalisation, and the availability of pertinent data on key variables of interest.

The rationale behind concentrating on African countries arises from the distinctive socio-economic conditions prevalent in this region, which markedly differ from those of developed nations. These conditions include challenges such as low levels of education, inadequate infrastructure, and limited access to finance, all of which have been identified as factors impeding economic growth in the African context (Gelb et al., 2014). By focusing on sub-Saharan African countries, the study aims to provide insights into the relationship between digitalisation and GDP within a context characterised by unique challenges and opportunities, contributing to a nuanced understanding of these dynamics.

3.5 Sample Size, Selection and Period

In this research, a purposive sampling method was used to select 10 African countries from sub-Saharan Africa. These countries were chosen deliberately to match the research goals and represent various levels of economic development and digitalization stages. This method was considered effective for addressing the research questions, focusing on the unique socio-economic conditions in Africa.

The study utilised data from the World Bank's economic indicators database spanning from 1998 to 2019, excluding 2020 due to outlier values linked to the COVID-19 pandemic. The sample of 10 countries was carefully selected to be representative of sub-Saharan Africa, considering diverse economic development levels and stages of digitalization. Each country represented a specific sub-region and contributed significantly to the region's GDP. Gelb et al. (2014) noted the distinct conditions of African countries for economic analysis. The inclusion of countries at different developmental stages allowed for a more comprehensive examination of the relationship between digitalization and economic growth. According to the World Bank (2021), these 10 countries constituted approximately 50% of the region's GDP in 2019. The exclusion of 2020 data due to the pandemic was justified to maintain data integrity.

The study period and the number of data points enabled the use of various analytical techniques, including trend analysis, time series regression, and statistical tests like correlation and cointegration.

3.6 Data Collection and Analysis

3.6.1 *Data Collection*

The primary source of data for this analysis was secondary data from the World Bank database of development indicators. This dataset included annual data on GDP, number of mobile users, percentage of internet users as a proportion of the population, population and manufacturing value add. To calculate the number of internet users, the percentage of internet users was multiplied by the population. Table 4 below shows the variables with links to the datasets.

Table 4 Variables and the data source links.

Variable Name	**Database link**
GDP	GDP- https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=BW
Mobile Subscriptions	https://data.worldbank.org/indicator/IT.CEL.SETS?locations=BW
Internet Users = %Internet users in Population * Population	Population: https://data.worldbank.org/indicator/SP.POP.TOTL?locations=BW % Internet users = https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=BW
Manufacturing Value Add	https://data.worldbank.org/indicator/NV.IND.MANF.CD?locations=BW

The four datasets were merged into a single Excel file with five columns: Year, GDP (dependent variable), Mobile, Internet Access, Broadband and Manufacturing Value Add (independent variables). The growth rates of all variables were then calculated.

3.6.2 *Data Analysis*

In this study, data was classified according to research constructs such as independent variables representing digitalisation data, the control variable to control for industrial effects of GDP, and the dependent variable. The data was coded in Excel and transferred to Python open-source data analysis tool. Various statistical tests such as timeseries regression such as pooled OLS and VAR were used to understand the relationship between independent and dependent variables. The study also employed trend analysis and descriptive statistics and cluster analysis.

To begin with all variables were changed into growth rates and tested for stationarity. Where the variable was not stationary, transformation techniques were applied and then an appropriate method was used to fit the data. Shrestha et al. (2018) proposed a selection technique as depicted in figure 3 below to deal with time series variables.

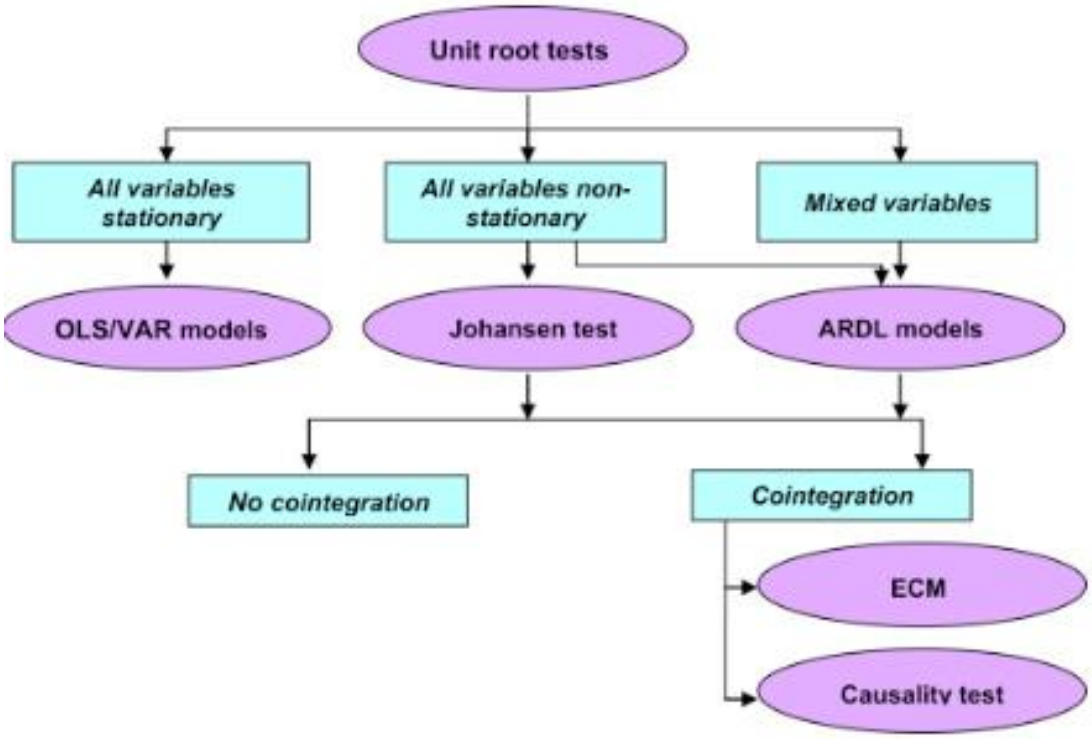


Figure 3 Time series analysis techniques (source : Shrestha et al, 2018)

Figure 3 below shows the process used in this study to conduct data analysis which was a partial adaptation of Shrestha et al (2018).

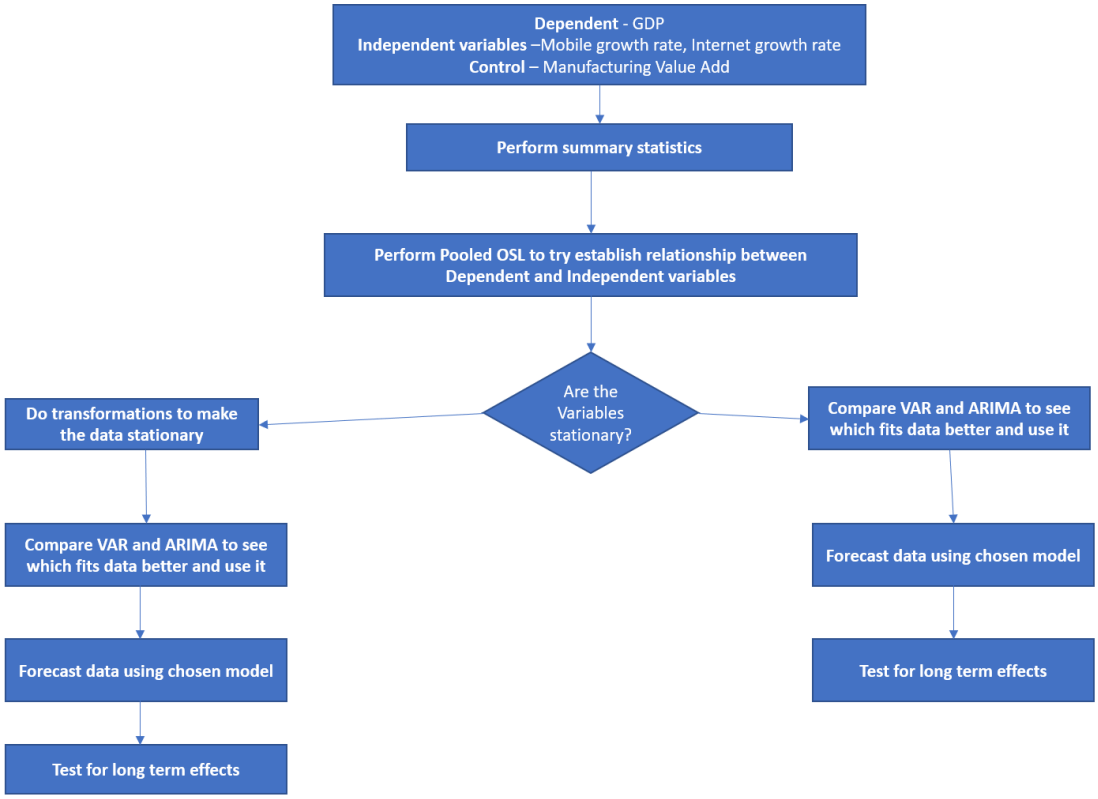


Figure 4 Data analysis process used in this study.

3.6.3 *Data Reliability and Validity*

The project utilised secondary data from the World Bank database, which is known for its reliability and dependability. The World Bank obtains data from credible sources such as government agencies, house-to-house surveys, and well-established organizations like the International Telecommunications Union (ITU), which specializes in information and communication technologies. The data is also publicly available, enabling future researchers to validate and verify the results of the study.

To ensure the validity of the research model and achieve its intended objectives, the study employed established relationship testing techniques such as time series regression, trend analysis and other statistical techniques such as

correlation analysis, co-integration tests and cluster analysis. The time series regression techniques and Pearson Correlation Coefficient, a commonly used correlation coefficient, was utilised to test the relationships between variables. Previous studies have also employed this coefficient to establish relationships between variables (Bennouna & Hebil, 2016; Wang et al., 2015; Ball & French, 2021; Marcu et al., 2015). To determine which variables had the most significant influence on the dependent variable, GDP, Pooled OLS regression methods were used. Multiple linear regression was deemed appropriate as it could handle multiple variables.

3.6.4 *Research Strategy*

The research strategy involves a systematic approach to data analysis, incorporating time series regression, trend analysis, and various statistical tests. Growth rates were employed to ensure stationarity, and the Pooled OLS regression model allowed for an in-depth exploration of the relationships between digitalization and GDP.

3.7 Limitations of the study

This study acknowledges notable limitations that warrant consideration. A primary limitation stems from the constrained sample size, attributed to limited data availability. This constraint may compromise the robustness of inferences, especially when employing time-series techniques, leading to diminished confidence levels. To mitigate this limitation, the study expanded the dataset, now encompassing data from a total of 10 countries, thereby surpassing the initially proposed scope.

Another limitation involves the exclusion of variables serving as proxies for digitization, such as digital skills, cloud technologies, and AI, due to unavailability of data. The analysis did not incorporate additional influential factors affecting GDP, such as education levels and access to finance.

The critique regarding the sole reliance on manufacturing value added as a control variable is and it is acknowledged that various factors, including inflation, interest rate, and governance and regulatory indicators, were not included in the model. To address this concern, future iterations of the model could incorporate these variables, particularly drawing from reliable sources like World Governance Indicators. The measures of data digitization used in the study are also acknowledged as a concern, and it is understood that their appropriateness needs to be unequivocally justified.

Moreover, the exclusion of the year 2020 is justified due to the unprecedented disruptions caused by the COVID-19 pandemic. While the application of standard statistical methods is recognized in economic research, there is acknowledgment that further analyses could enhance result robustness. Regrettably, due to constraints in scope and time, alternative statistical models and sensitivity analyses were not conducted, which could be considered in future research endeavours.

3.8 Ethical considerations

As stated in the data collection section of the proposal, this study solely relied on publicly available secondary data from World Bank development indicators online databases and did not involve any human subjects, thus no ethical concerns were present. Additionally, the university's ethics committee granted an ethics waiver.

3.9 Statistical Tests and Results

Firstly, the study began with a descriptive analysis of the sample data, which included the calculation of summary statistics such as means and standard deviations. Additionally, trend analysis over time was conducted for the various variables.

Secondly, the study employed various statistical tests to analyse the data. Time series regression, correlation analysis, including Pearson correlation coefficient and scatterplots, was used to investigate the relationships between variables. Time series analysis techniques such as stationarity tests and cointegration tests were applied to analyse the growth rates of both dependent and independent variables. The use of growth rates for time series analysis was preferred as it allows for easier stationarity of the time series data, unlike when using absolute values.

Thirdly, the study utilised a Pooled OLS regression analysis model, with GDP as the dependent variable and internet users, mobile cellular subscriptions, and manufacturing value added as independent variables. The significance and effect of the control on the other independent variables were tested through the Pooled OLS model. Cluster analysis was also applied to enhance the analysis.

3.10 Consistency Matrix

The consistency matrix is provided in Table 5. The consistency matrix was used to ensure that there was consistency between the problem statement, the research objectives, the literature review, the proposed data collection method, and the data analysis method.

3.11 Summary

In summary, during the data exploration phase, a trend analysis of all variables was conducted, and summary statistics were described. The variables, including GDP growth rate as the dependent variable, Mobile growth rate and Internet growth rate as independent variables, and Manufacturing Value Add growth rate as a control variable, were tested for stationarity.

Time series regression and correlation analysis was conducted to determine the significance of the relationships between GDP and all variables. Additionally, cointegration tests were performed to evaluate the long-term effects of these relationships. Notably, cointegration does not require the series to be stationary.

Furthermore, to conduct for time series analysis and gain a deeper understanding of the relationship, the growth rates of all variables were transformed to achieve stationarity. The findings were then analysed together to establish a comprehensive understanding of the relationship between GDP and digitalisation.

To evaluate the impact of the control variable on the model, Pooled OLS models were estimated both with and without the inclusion of Manufacturing Value Add. A thorough analysis was then conducted to assess its impact on the relationship between GDP and the digitalisation variables (Mobile and Internet).

Table 5 Consistency table: research questions, propositions, data collection and data analysis

Problem Statement: The research problem identified in this study is the limited understanding of the impact of digitalisation on the economic growth and development of SSA. While there has been an increasing adoption of digital technologies on the continent, there is still a lack of empirical research examining the relationship between digitalisation and GDP in SSA. This gap in knowledge limits the ability of policymakers and businesses to effectively utilise digital technologies to drive economic growth and development on the continent. Thus, this study seeks to address this research problem by investigating the relationship between digitalisation data and GDP through a quantitative research methodology.				
Objective	**Review**	**Proposition**	**Data Collection detail**	**Analysis**
Establish if there is a relationship between Internet Usage data and GDP per capita in SSA	Salahuddin and Gow (2016), Clarke et al. (2015), Harb (2017), Fernández-Portillo et al (2020), Katz et al (2020), Watanabe et al	The literature reviewed shows that there is a correlation between Internet Usage and an uplift in economic growth (GDP per capita).	World Bank database of economic indicators	Time series regression analysis, co-integration and Pooled OLS regression, Correlation analysis & cluster analysis

	(2018), Zhang (2021), Yu (2022)			
Establish if there is a relationship between Mobile penetration data and GDP per capita SSA	Miyajima (2022), Fosu (2011), Hasbi and Dubus (2020), Kongaut and Bohlin (2016), Myovella et al (2020), Donou-Adonsou (2019), Kanyam et al. (2017), Kim et al. (2021)	The literature reviewed shows that there is a correlation between Mobile Phones penetration and usage and an uplift in economic growth (GDP per capita).	World Bank database of economic indicators	Time series regression analysis, co-integration and Pooled OLS regression, Correlation analysis & cluster analysis
To investigate the effect of manufacturing value, add as a control variable on the relationship between Mobile and Internet users and GDP in SSA.	Kumar and Kumar (2010), Singh (2013), Salim (2015), Wang (2016), Hosseinzadeh (2018)	The literature reviewed showed that using manufacturing value-added control variable can provide insight into the causal relationship	World Bank database of economic indicators	Pooled OLS regression

		between GDP and digitalisation.		

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

This chapter commences with an overview of the statistics and trend analysis of various variables. It then conducts a range of statistical analyses utilising time series techniques. The results of the first objective, which sought to establish the relationship between GDP and Internet usage data, are subsequently presented. The results of the second objective, which aimed to determine the relationship between GDP and mobile penetration data, are then presented. Finally, the impact of manufacturing value add as a control on the relationship between dependent and independent variables is discussed. Appendix B contains details of the data analysis conducted in Python.

4.2 Descriptive Statistics

Descriptive statistics were used to analyse the growth rates and absolute values of the time series data. These values were also used in other techniques, such as correlation analysis, to understand the trends. Time series analysis was conducted using data from different countries in Sub-Saharan Africa (SSA) to increase the number of data points and improve the statistical significance of the results. The data was imported from two Excel sheets into Pandas DataFrames. One sheet contained the absolute values, while the other contained the growth rates.

Using growth rates in time series analysis has advantages because it increases the stationarity of the data, making it easier to transform non-stationary data into a stationary format. Stationary data does not have trends or seasonality, making it easier to analyse and model. In contrast, non-stationary data has trends or seasonality, which can make it difficult to analyse and model. By using growth rates, non-stationary data can be transformed into a stationary form by dividing each data point by its previous value.

4.2.1 *Summary Statistics of the growth rates*

a. *Descriptive Statistics of the growth rates*

The summary statistics of the growth rates values of both the independent and dependent variables from the 10 SSA countries during the period from 1999 to 2019 are presented in Table 6.

Table 6 summary statistics of the independent and dependent variables

Variable	Internet Users	Mobile Users	Manufacturing Value Add	GDP
Count	230	230	230	230
Mean	0.443683	0.509726	0.100220	0.094619
Std	0.685520	0.885782	0.293387	0.171335
Min	-1.000000	-0.253755	-0.513072	-0.428561
25%	0.116819	0.085906	-0.025501	-0.005473
50%	0.214160	0.240626	0.064669	0.077422
75%	0.490548	0.590333	0.185975	0.164063
Max	4.779053	7.882033	2.919965	0.902421

The descriptive statistics in table 6 provide insights into the distribution and characteristics of the four variables:

Internet Users growth rate: The mean growth rate is 0.443683, with a standard deviation of 0.685520. This suggests that there is a moderate variation in the growth rates, with some countries experiencing a decrease in internet users and others experiencing a substantial increase.

Mobile Users growth rate: The mean growth rate is 0.509726, with a standard deviation of 0.885782. This suggests that there is greater variability in the growth rates for mobile users than for internet users.

Manufacturing Value Add growth rate: The mean growth rate is 0.100220, with a standard deviation of 0.293387. This suggests that there is moderate variability in the growth rates for manufacturing value add.

GDP growth rate: The mean growth rate is 0.094619, with a standard deviation of 0.171335. This suggests that there is moderate variability in the growth rates for GDP.

In summary, the descriptive statistics presented above provide a summary of the distribution and key characteristics of the four variables. They shed light on the central tendency, variability, and range of the data, and serve as a foundation for further analysis and understanding of the data.

b. ***Correlation Matrix and Scatter Matrix***

The correlation matrix shown in figure 5 and the scatter matrix in figure 6 below summarises the relationships between variables in the dataset.

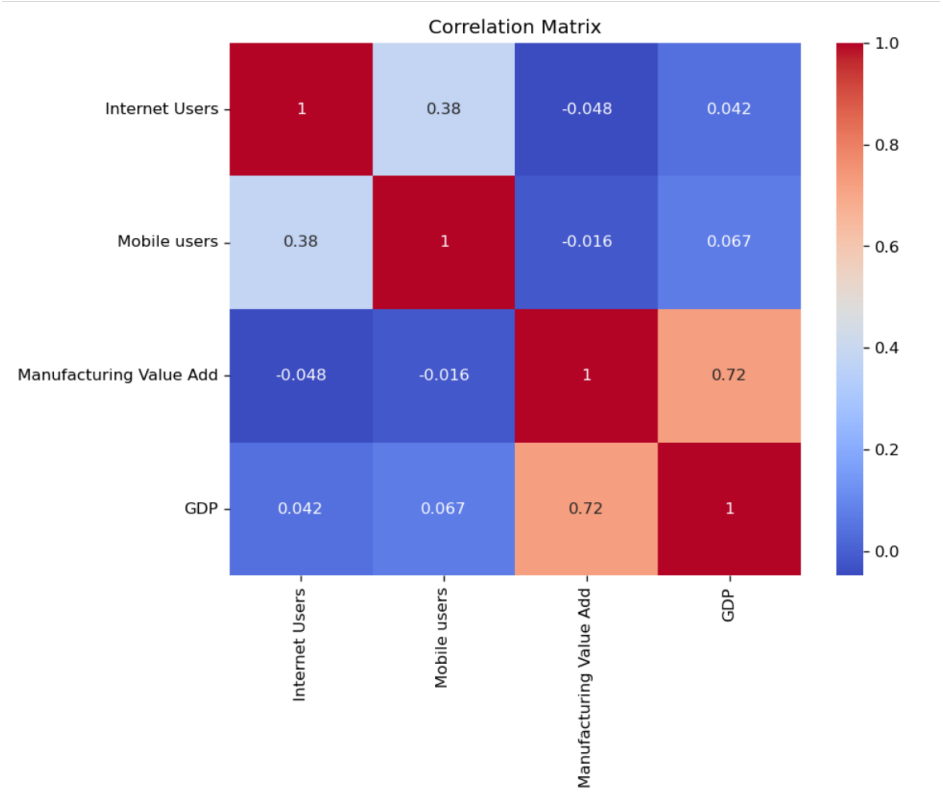


Figure 5 Correlation Matrix.

The correlations were calculated using Pearson's correlation coefficient, which measures the strength and direction of the linear relationship between two variables.

Internet Users and Mobile Users: The correlation between Internet Users and Mobile Users is moderate and positive (0.384546). This suggests that as the

number of internet users increases, there tends to be a moderate increase in the number of mobile users.

Internet Users and Manufacturing Value Add: The correlation between Internet Users and Manufacturing Value Add is weakly negative (-0.047747). This indicates that there is a weak inverse relationship between the two variables. In other words, as the number of internet users increases, there is a slight decrease in the manufacturing value added.

Internet Users and GDP: The correlation between Internet Users and GDP is weakly positive (0.041748). This suggests that there is a weak association between the two variables. In other words, as the number of internet users increases, there is a slight increase in the GDP.

Mobile Users and Manufacturing Value Add: The correlation between Mobile Users and Manufacturing Value Add is very weakly negative (-0.016386). This indicates that there is almost no relationship between the two variables.

Mobile Users and GDP: The correlation between Mobile Users and GDP is weakly positive (0.067496). This suggests that there is a slight positive association between the two variables. In other words, as the number of mobile users increases, there is a slight increase in the GDP.

Manufacturing Value Add and GDP: The strongest correlation in the matrix is between Manufacturing Value Add and GDP (0.724709). This strong positive correlation suggests that changes in the manufacturing value added are closely related to changes in the GDP. An increase in the manufacturing value added tends to correspond to a higher GDP.

In summary, the correlation matrix provides insights into the relationships among these variables. It indicates that the manufacturing value added is strongly associated with the GDP, while the correlations involving internet users and mobile users are relatively weak or negligible.

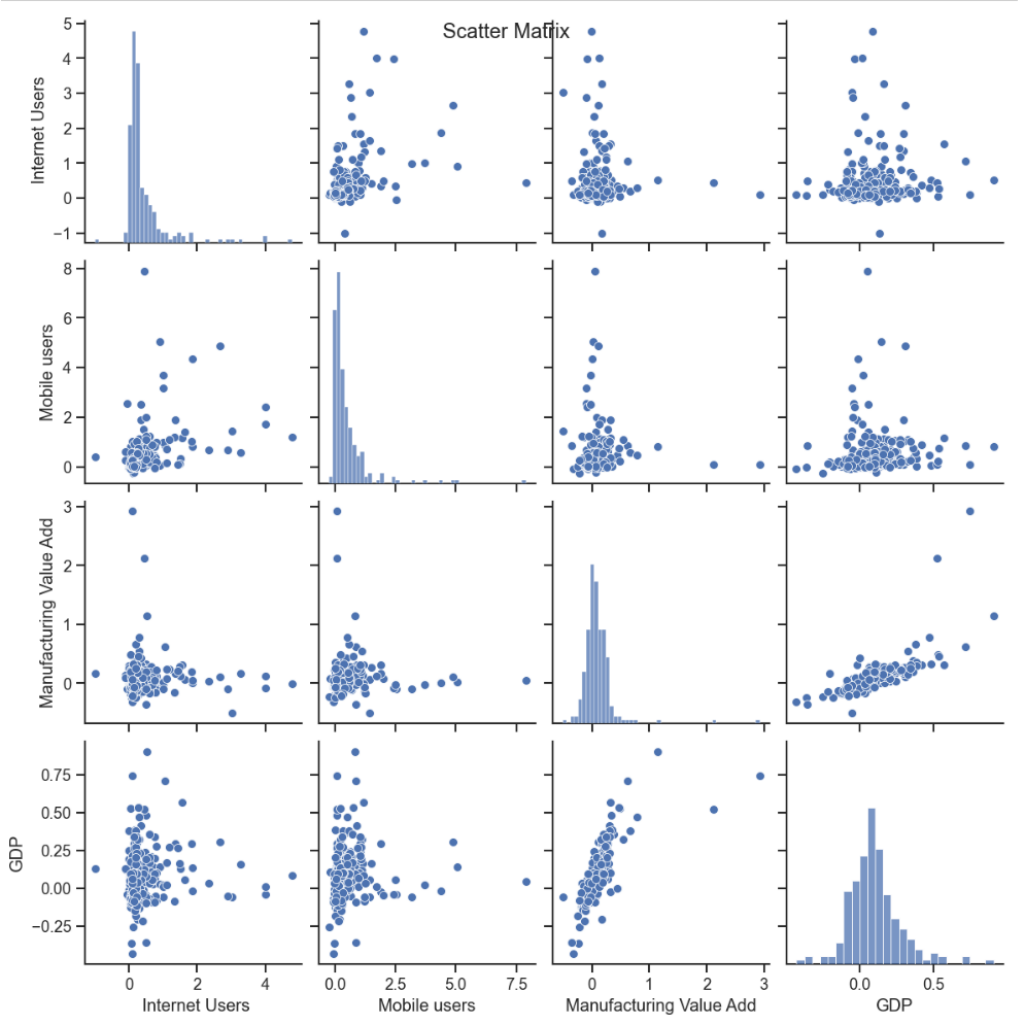


Figure 6 Scatter Matrix.

4.2.1 *Trend Analysis – Real Values*

As depicted in Figure 7, a trend analysis of all variables for the sample countries reveals an upward trajectory for nearly all measures.

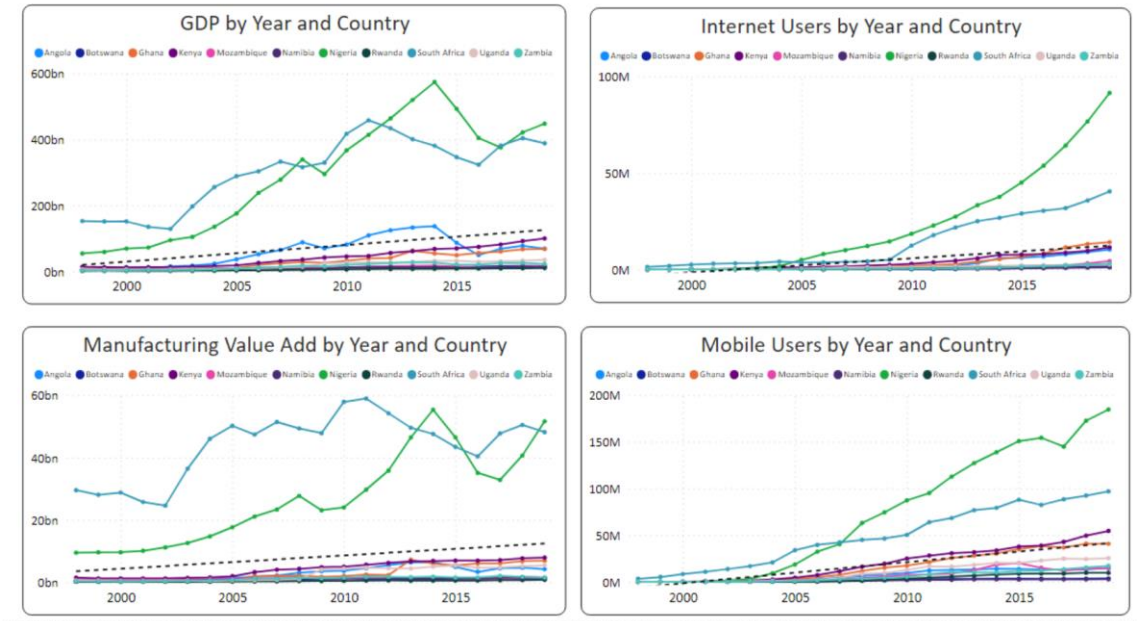


Figure 7 Trend Analysis of GDP of various countries

The rest of this trend analysis section focuses on individual variables.

a. ***Trend Analysis – GDP***

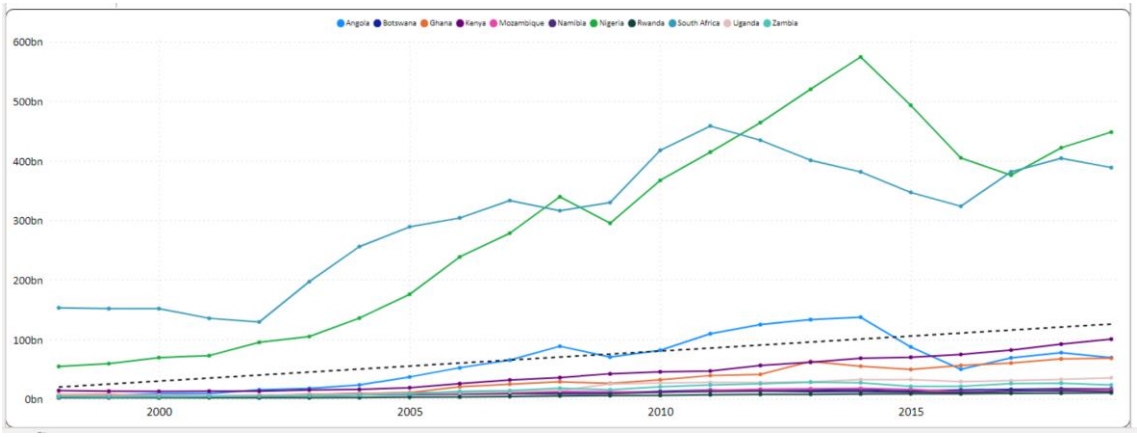


Figure 8 GDP Trend Analysis

Overall, the data shows that the GDP of the SSA countries has been growing steadily in recent years with Nigeria and South Africa being the two biggest economies.

b. ***Trend Analysis – Internet users***

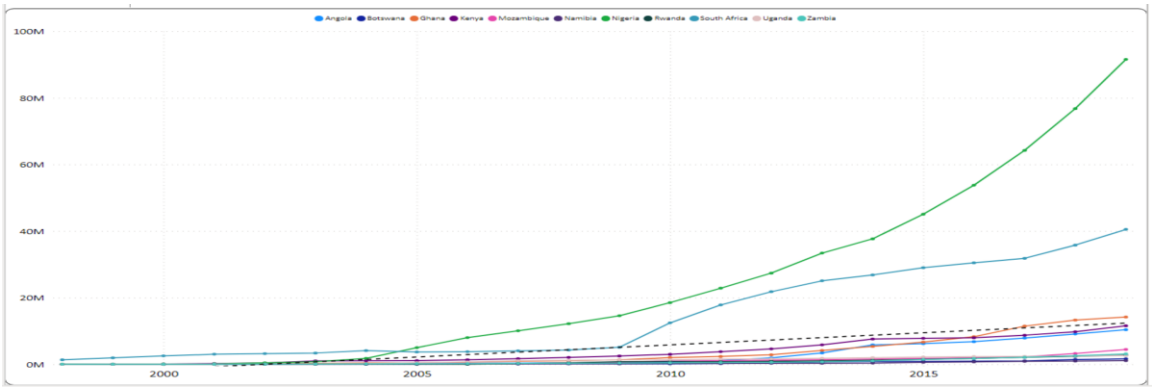


Figure 9 Internet Users Trend Analysis

Overall, the data shows that the number of internet users in SSA has increased significantly over the past 20 years as shown in graph in figure 9 above.

c. *Trend Analysis – Mobile Users*

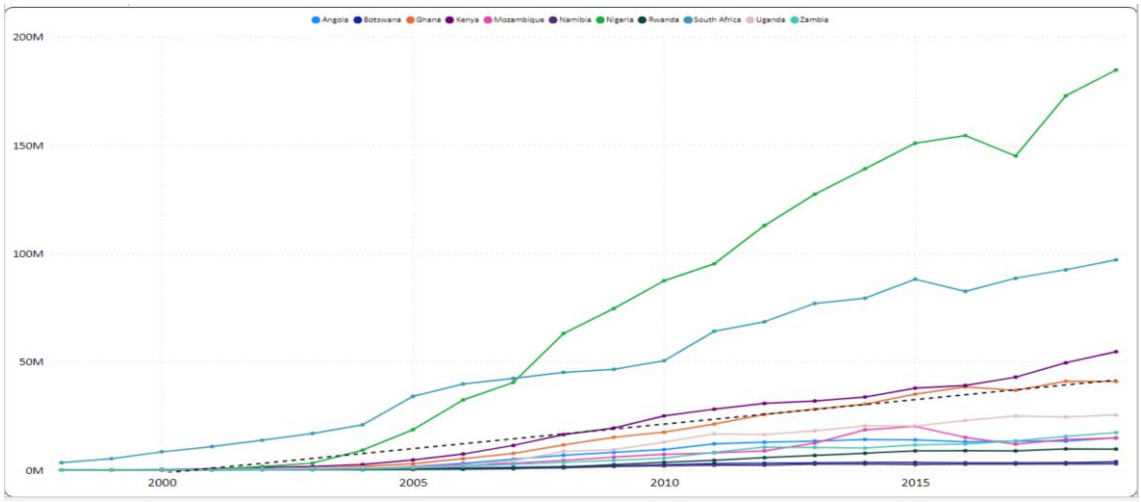


Figure 10 Mobile Users Trend Analysis

Mobile users in SSA have also increased significantly over the past 20 years as shown in the graph above in figure 10 with Nigeria and South Africa showing the highest numbers in terms of volumes.

d. *Trend Analysis – Manufacturing Value Add*

An analysis of the data indicates in the graph in figure 11 shows significant variations in manufacturing value add across countries and time periods. For example, Angola exhibits a consistent increase in manufacturing value add over

time. Similarly, upward trends are observed in countries such as Botswana, Ghana, and Kenya, suggesting growth in their respective manufacturing sectors.

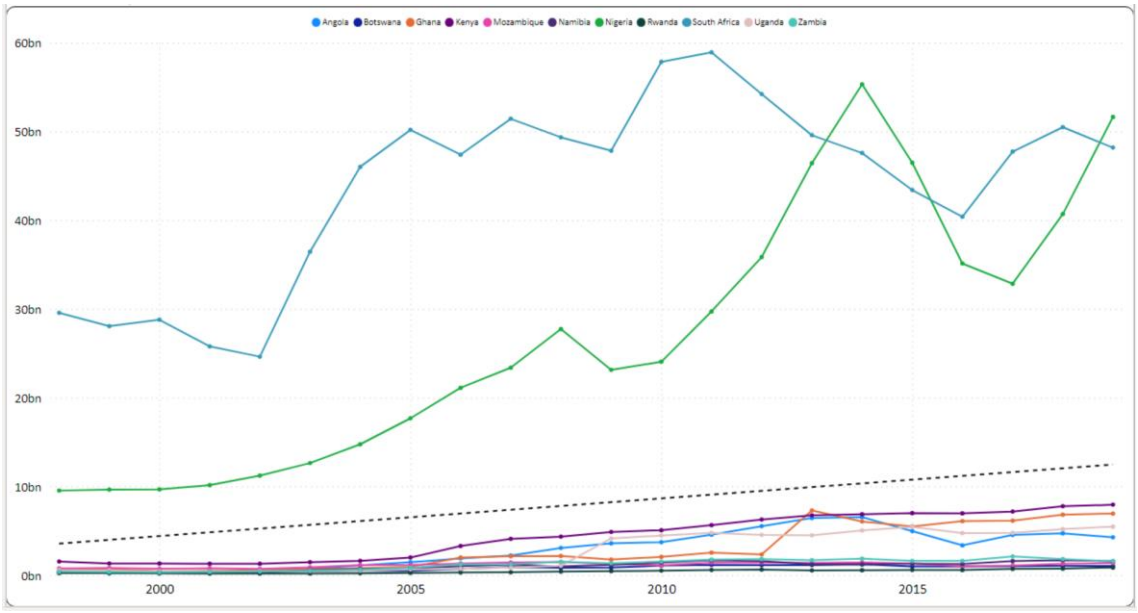


Figure 11 Manufacturing Value Add Trend Analysis

4.2.2 *Trend Analysis – Growth Rates*

The growth rates of GDP, internet users, mobile users, and manufacturing value add in African countries were analysed. The results showed that the growth rates of these variables varied significantly across countries and years, as shown in the graphs in Figure 12.

GDP growth rates fluctuated widely among the countries, with Angola experiencing the most significant variations. Botswana's GDP growth rate remained relatively stable, while Ghana exhibited both positive and negative growth rates.

Internet growth rates also varied significantly, with some countries experiencing high growth rates and others experiencing negative growth rates. Angola and Rwanda experienced the highest growth rates, while Rwanda also experienced a negative growth rate in 2000.

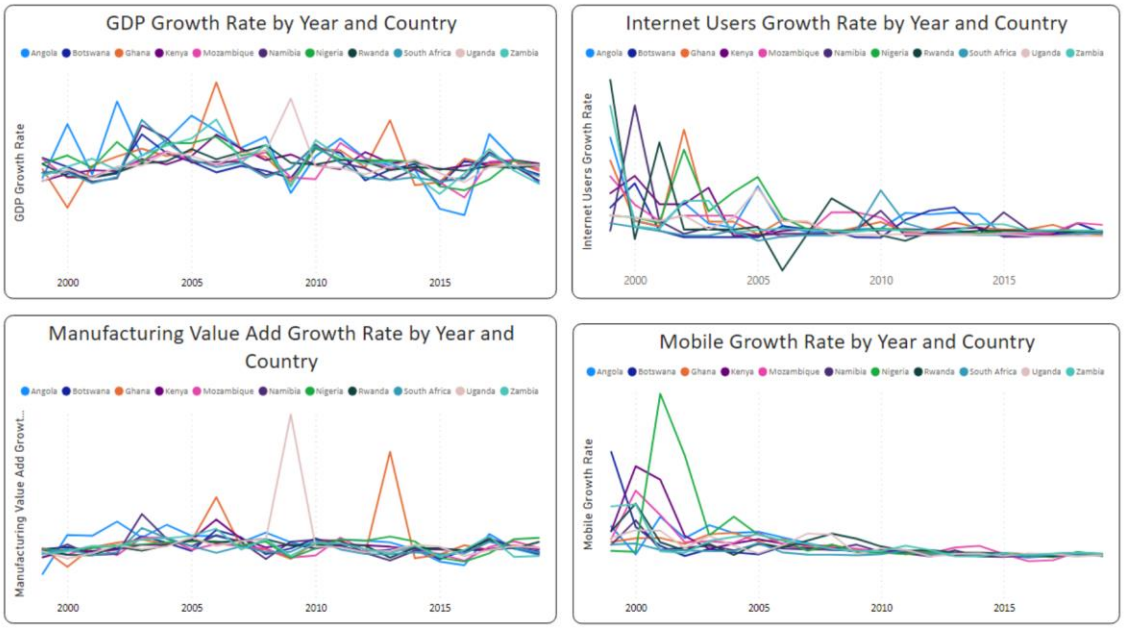


Figure 12 Trending Analysis of different growth rates

Mobile growth rates exhibited similar variations, with Angola experiencing the most significant growth followed by Botswana. Ghana demonstrated relatively consistent growth, while Kenya and Mozambique experienced substantial growth. Nigeria and Rwanda also experienced notable growth, while South Africa and Uganda demonstrated more moderate growth.

Manufacturing value add growth also varied significantly, with Angola experiencing a significant decline followed by a recovery. Botswana exhibited relatively stable growth, while Ghana experienced mixed results. Kenya,

Mozambique, Namibia, Nigeria, Rwanda, South Africa, Uganda, and Zambia also demonstrated varying degrees of growth fluctuations.

These findings suggest that the economic performance of African countries varied significantly during the period analysed.

4.2.3 *Statistical Analysis*

a. *Stationarity Tests of Growth rates*

Table 7 presents the results of the Augmented Dickey-Fuller test for stationarity on each variable in the data set. The test statistic, p-value, and number of lags used are included. The null hypothesis of the test is that the data is non-stationary. A p-value less than 0.05 indicates statistical significance and allows for the rejection of the null hypothesis in favour of the alternative hypothesis that the data is stationary.

The statistical analysis conducted on the variables Internet Users, Mobile Users, Manufacturing Value Add, and GDP shows that all variables exhibit stationary behaviour. The test statistics for the stationarity tests on these variables are significantly lower than the critical values at the 1%, 5%, and 10% significance levels. The corresponding p-values provide strong evidence against the null hypothesis of non-stationarity.

Table 7 Stationarity Tests of the variables

Variable	Test Statistic	P-value	Critical Values (1%)	Critical Values (5%)	Critical Values (10%)	Stationary
Internet Users	-9.252825	1.476456e-15	-3.459361	-2.874302	-2.573571	True
Mobile Users	-8.791299	2.236822e-14	-3.459361	-2.874302	-2.573571	True
Manufacturing Value Add	-14.230428	1.600077e-26	-3.459233	-2.874245	-2.573541	True
GDP	-7.852376	5.556952e-12	-3.460849	-2.874953	-2.573919	True

These results suggest that the variables do not possess a trend or systematic changes over time, providing a stable basis for time series analysis and related investigations.

The next section of the study thus fits a pooled OLS time series regression model to the data.

b. *Pooled OLS Regression*

The Pooled OLS regression results shown in table 8, show that the following variables are significant predictors of GDP:

Internet users: A 1% increase in internet users is associated with a 0.0135% increase in GDP.

Mobile users: A 1% increase in mobile users is associated with a 0.0114% increase in GDP.

Table 8 Pooled OLS Regression Results

OLS Regression Results

Dep. Variable:	GDP	R-squared:	0.534
Model:	OLS	Adj. R-squared:	0.528
Method:	Least Squares	F-statistic:	86.32
Date:	Sat, 03 Jun 2023	Prob (F-statistic):	2.99e-37
Time:	12:57:03	Log-Likelihood:	167.70
No. Observations:	230	AIC:	-327.4
Df Residuals:	226	BIC:	-313.7
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0402	0.010	3.991	0.000	0.020	0.060
Internet Users	0.0135	0.012	1.096	0.274	-0.011	0.038
Mobile users	0.0114	0.010	1.193	0.234	-0.007	0.030
Manufacturing Value Add	0.4253	0.027	16.019	0.000	0.373	0.478

Omnibus:	26.743	Durbin-Watson:	1.712
Prob(Omnibus):	0.000	Jarque-Bera (JB):	107.145
Skew:	-0.299	Prob(JB):	5.42e-24
Kurtosis:	6.290	Cond. No.	4.72

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Manufacturing value add: A 1% increase in manufacturing value add is associated with a 0.4253% increase in GDP.

The model has an adjusted R-squared of 0.528, which means that the variables in the model explain 52.8% of the variation in GDP. The F-statistic is 86.32, which is significant at the 0.000 level, indicating that the model is a good fit for the data.

The Durbin-Watson statistic is 1.712, which is close to 2, indicating that there is no autocorrelation in the residuals. The Jarque-Bera statistic is 107.145, which is significant at the 0.000 level, indicating that the residuals are not normally distributed.

Overall, the results of the Pooled OLS regression suggest that internet users, mobile users, and manufacturing value add are predictors of GDP. However, the residuals of the model are not normally distributed, which could impact the accuracy of the model's predictions.

c. *Time series forecasting*

i. ARIMA Vs. VAR

To determine the most appropriate model for the time series data, a comparison was conducted between VAR and ARIMA models. The results of this comparison are presented in Table 9.

Table 9 ARIMA Vs. VAR results

Model	AIC	BIC
VAR	-8.214249996046421	-7.91436161145653
ARIMA	-158.88868210523685	-148.58751609457414

Export to Sheets

In the analysis conducted, both VAR and ARIMA models were evaluated using the AIC and BIC criteria to assess the goodness of fit. The VAR model yielded an AIC value of -8.21425 and a BIC value of -7.91436. In contrast, the ARIMA model yielded significantly lower AIC and BIC values of -158.88868 and -148.58752, respectively. These results suggest that the ARIMA model provides a better fit to the data compared to the VAR model. Therefore, it can be inferred that the ARIMA model is the preferred choice for modelling and forecasting the GDP growth rate in this analysis.

The AIC and BIC criteria are both measures of how well a model fits the data. The lower the AIC or BIC value, the better the fit. In this case, the ARIMA model has significantly lower AIC and BIC values than the VAR model, which suggests that the ARIMA model provides a better fit to the data.

The results of this analysis indicate that the ARIMA model is the preferred choice for modelling and forecasting the GDP growth rate. This is because the ARIMA model has a better fit to the data than the VAR model.

ii. ARIMA Vs. AUTO ARIMA

Furthermore, the data was fit to both an ARIMA model through experimentation and an AUTO ARIMA model. The results from the two models were similar, indicating that either model could be used for forecasting with the similar levels of accuracy. The results of the ARIMA model are presented in Table 10, while the results of the AUTO ARIMA model are presented in Table 11.

Table 10 ARIMA Results

Variable	MAE	RMSE
GDP	0.1174	0.1504
Internet Users	0.4455	0.8547
Mobile Users	0.3629	0.4493
Manufacturing Value Add	0.1643	0.2169

The performance of the ARIMA model varies across the different variables. For GDP, the model yields a mean absolute error (MAE) of 0.1174 and a root mean square error (RMSE) of 0.1504. For Internet Users, the model produces a MAE of 0.4455 and an RMSE of 0.8547. For Mobile Users, the model's MAE is 0.3629 and the RMSE is 0.4493. For Manufacturing Value Add, the model exhibits a MAE of 0.1643 and an RMSE of 0.2169.

Overall, the ARIMA model achieves the lowest errors for Manufacturing Value Add, indicating better predictive accuracy for this variable. However, for Internet Users, the model exhibits higher errors, suggesting less accurate predictions.

The MAE and RMSE are both measure of how accurate a model is at predicting the target variable. The lower the MAE or RMSE value, the more accurate the model is. In this case, the ARIMA model has lower MAE and RMSE values for Manufacturing Value Add than for the other variables, which suggests that the model is more accurate at predicting Manufacturing Value Add.

The higher MAE and RMSE values for Internet Users suggest that the model is less accurate at predicting this variable. This may be because Internet Users is a

more volatile variable than Manufacturing Value Add, making it more difficult to predict.

Overall, the results of this analysis suggest that the ARIMA model is a good choice for forecasting Manufacturing Value Add, but it may not be as accurate for forecasting Internet Users.

Table 11 AUTO ARIMA Results

Variable	MAE	RMSE
GDP	0.1175	0.1505
Internet Users	0.4721	0.8608
Mobile Users	0.3593	0.4398
Manufacturing Value Add	0.1637	0.2169

The graphs below show the forecasts that were generated by the ARIMA model for all the four variables with blue representing being the training data, orange the test data and green the forecast data. Details of the analysis can be found in appendix B.

GDP

```
Variable: GDP
MAE: 0.1254327767399007
RMSE: 0.15882247597827598
```

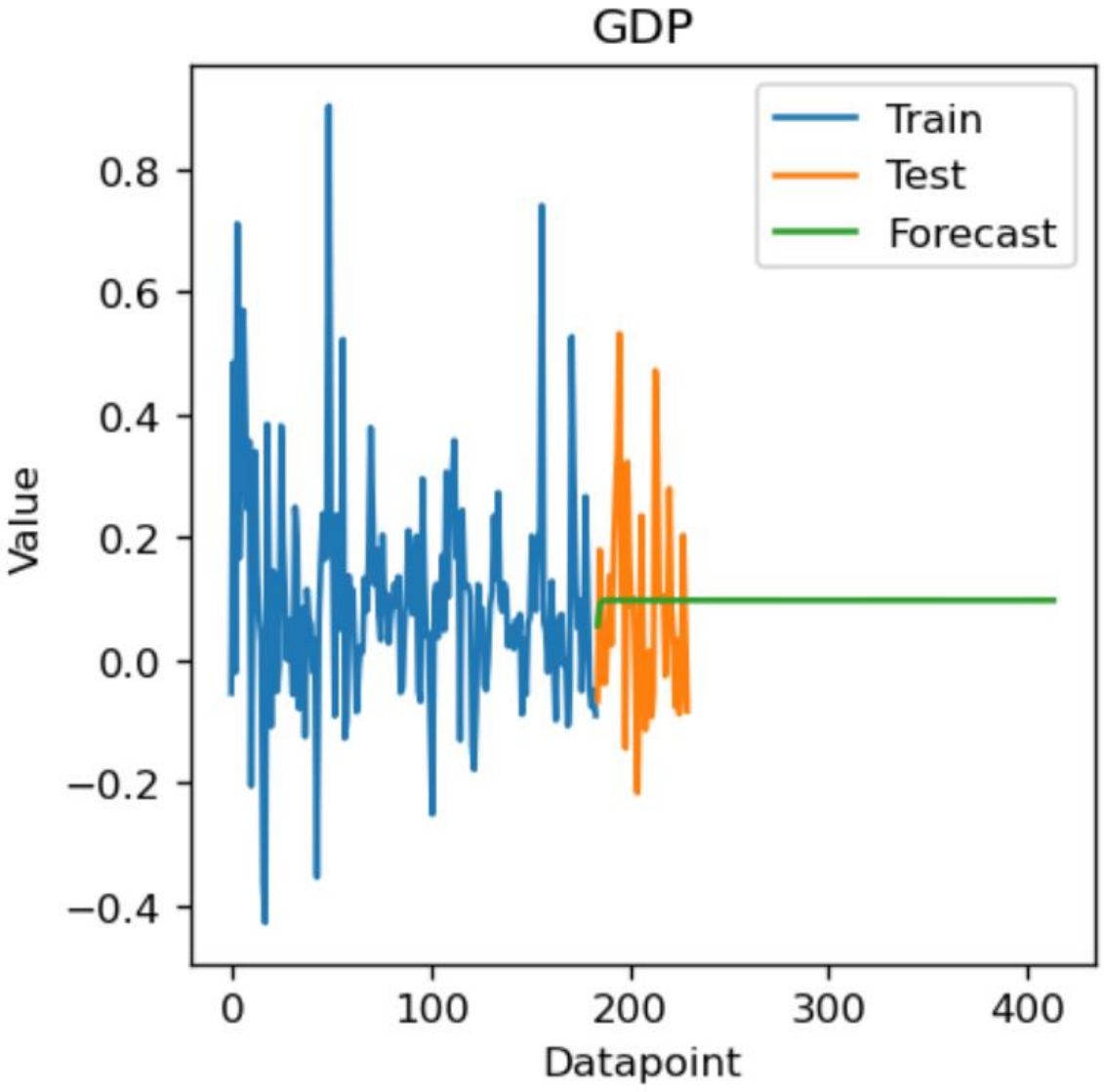


Figure 13 GDP ARIMA forecast.

Internet Users

```
Variable:  Internet Users
MAE: 0.3750744040333242
RMSE: 0.7998692118042761
```

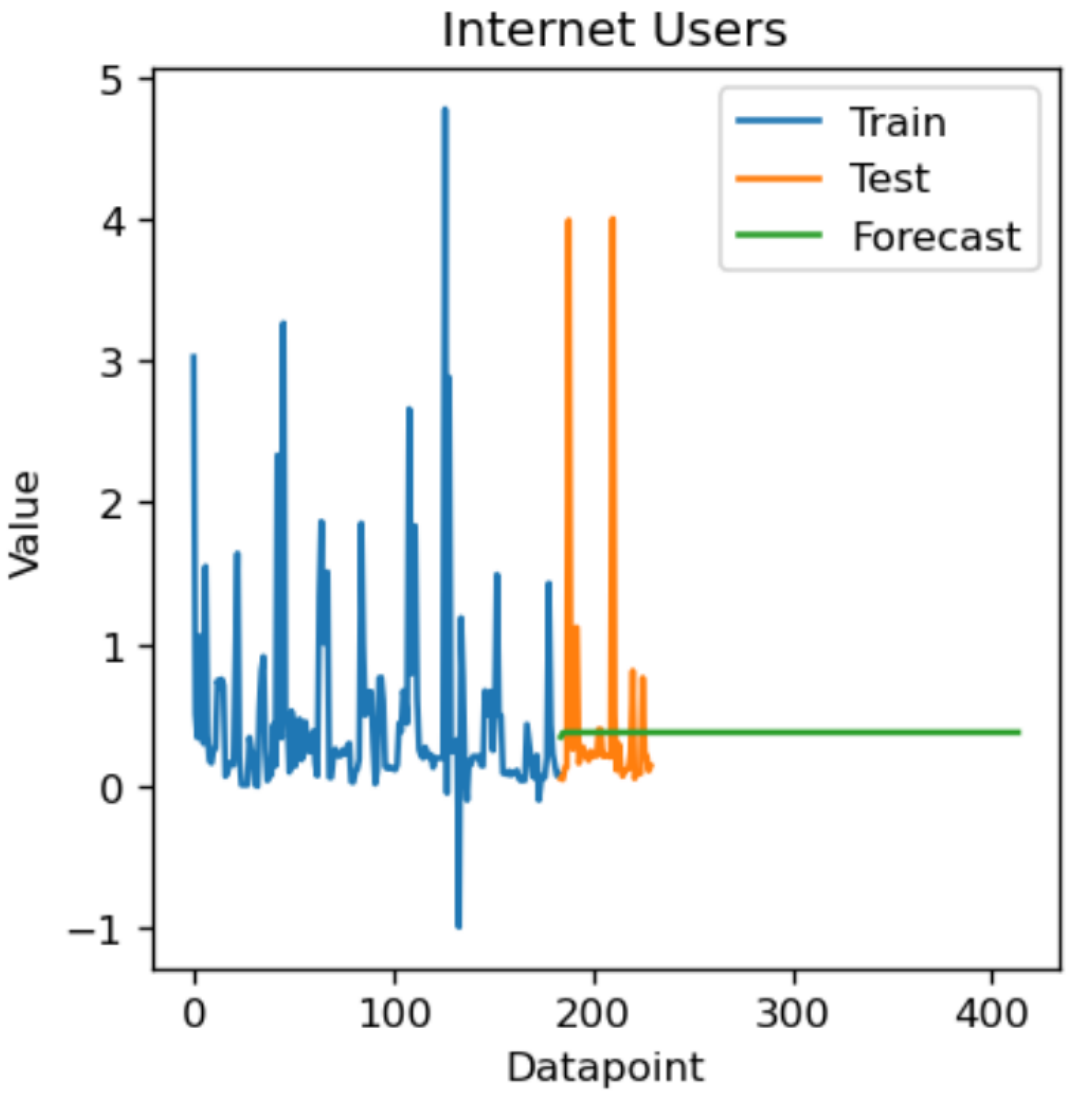


Figure 14 Internet ARIMA forecast.

Mobile Users

```
Variable: Mobile users
MAE: 0.41991264614585094
RMSE: 0.5679609615737553
```

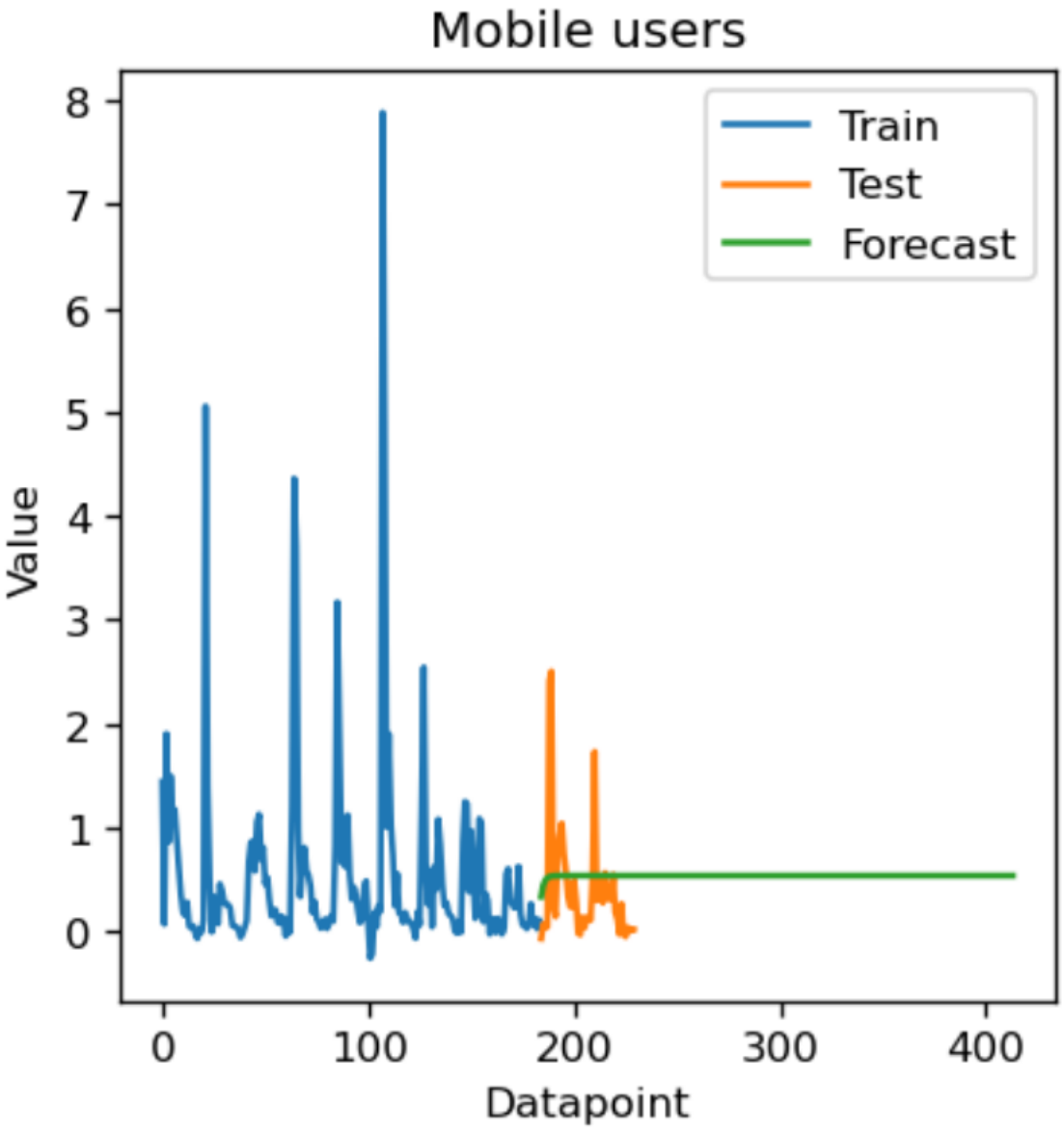


Figure 15 Mobile ARIMA forecast.

Manufacturing Value Add

```
Variable: Manufacturing Value Add
MAE: 0.1504841916983491
RMSE: 0.18855454180408865
```

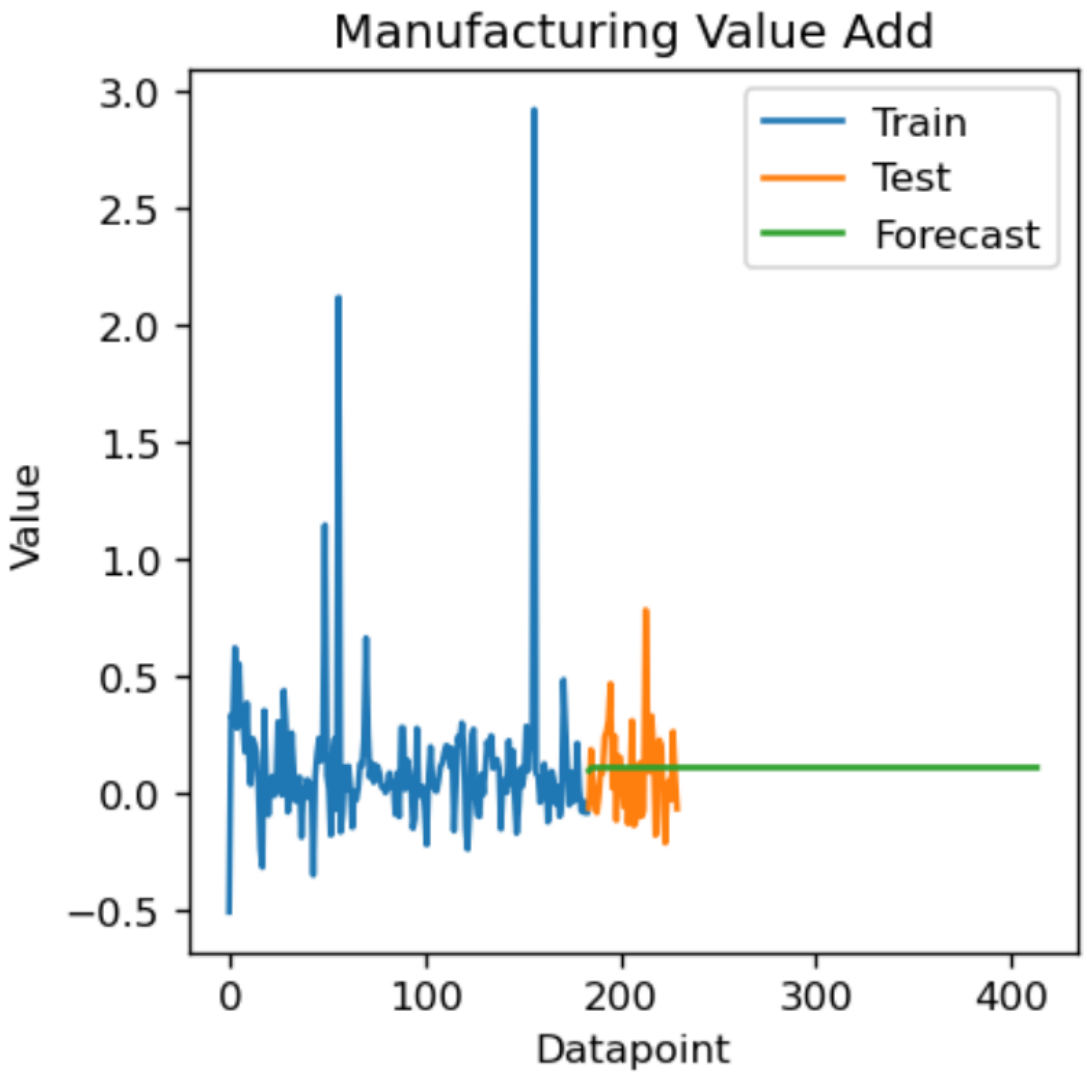


Figure 16 Manufacturing ARIMA forecast.

d. ***Co-Integration Analysis***

Table 12 Co- Integration test Results

```
Engle-Granger Test Results:
Test Statistic: -7.0516774434957314
P-value: 1.3417429024566884e-07
Critical Values:
        -4.723096928357583
        -4.145273795312828
        -3.8469299803588797
```

The Engle-Granger test was conducted to investigate the presence of cointegration between the variables and the results are shown in table 12 above. The test statistic of -7.0516774434957314 suggests strong evidence of cointegration. This finding is further supported by the p-value of 1.3417429024566884e-07, which indicates a very low probability of obtaining such results by chance.

The critical values provide a benchmark for comparing the test statistic. The values -4.723096928357583, -4.145273795312828, and -3.8469299803588797 represent different levels of significance. Since the test statistic falls below all the critical values, it provides additional support for the presence of cointegration.

In summary, the Engle-Granger test results provide strong evidence that the variables are cointegrated. This means that the variables have a long-run relationship and that changes in one variable can be expected to lead to changes in the other variable.

4.2.4 *Additional Analysis*

The different statistical methods described in the previous section produced mixed results. While ARIMA consistently outperformed other models, it was not sufficiently accurate to provide a conclusive answer to the relationship between GDP and digitalisation in SSA. As a result, more advanced algorithms and techniques were used, such as non-seasonal data (ETS AAN) and clustering. These techniques were implemented using the Microsoft Power BI Analytical tool.

a. *Exponential Smoothing and Pooled OLS*

A total of 230 data points were collected for all variables. Figure 17 shows the plot of these data points. The ETS AAN method was used to forecast the next 230 data points. A pooled OLS squares model was then fitted to the data to determine the relationship between the dependent variable (GDP) and the independent variables, including the influence of the control variable. The results of the pooled regression model are shown in table 13.

The pooled OLS regression results show that the following variables are predictors of GDP growth rate:

Internet users' growth rate: A 1% increase in internet users' growth rate is associated with a 0.0065% increase in GDP growth rate.

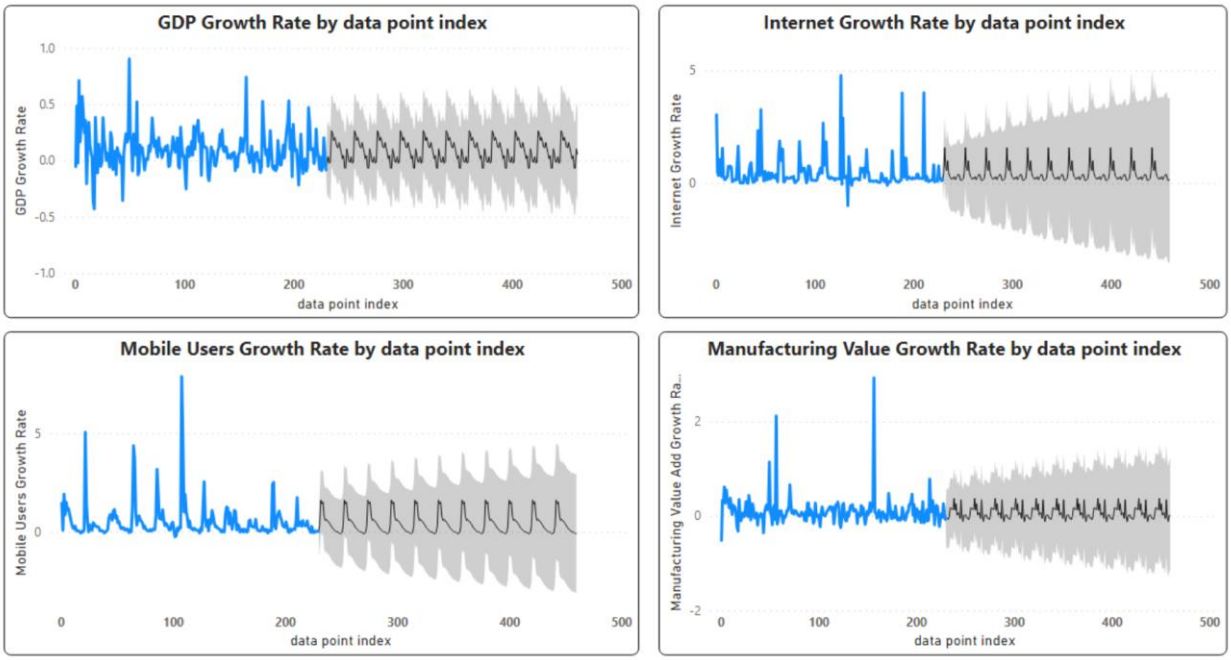


Figure 17 Exponential Smoothing and forecast in power BI.

Mobile users' growth rate: A 1% increase in mobile users' growth rate is associated with a 0.0247% increase in GDP growth rate.

Manufacturing value add: A 1% increase in manufacturing value add is associated with a 0.4179% increase in GDP growth rate.

The model has an adjusted R-squared of 0.499, which means that the variables in the model explain 49.9% of the variation in GDP growth rate. The F-statistic is 113.0, which is significant at the 0.000 level, indicating that the model is a good fit for the data.

Table 13 Pooled OLS Results after exponential smoothing

OLS Regression Results

Dep. Variable:	GDP Growth rate	R-squared:	0.503
Model:	OLS	Adj. R-squared:	0.499
Method:	Least Squares	F-statistic:	113.0
Date:	Sun, 18 Jun 2023	Prob (F-statistic):	1.42e-50
Time:	14:40:03	Log-Likelihood:	284.52
No. Observations:	339	AIC:	-561.0
Df Residuals:	335	BIC:	-545.7
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0539	0.008	6.630	0.000	0.038	0.070
Internet Users Growth rate	0.0065	0.011	0.609	0.543	-0.015	0.028
Mobile Users Growth rate	0.0247	0.010	2.467	0.014	0.005	0.044
Manufacturing Value Add	0.4179	0.023	18.143	0.000	0.373	0.463

Omnibus:	47.250	Durbin-Watson:	1.671
Prob(Omnibus):	0.000	Jarque-Bera (JB):	195.203
Skew:	-0.496	Prob(JB):	4.09e-43
Kurtosis:	6.583	Cond. No.	5.13

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The Durbin-Watson statistic is 1.671, which is close to 2, indicating that there is no autocorrelation in the residuals. The Jarque-Bera statistic is 195.203, which is significant at the 0.000 level, indicating that the residuals are not normally distributed.

Overall, the results of the OLS regression suggest that internet users' growth rate, mobile users'; growth rate, and manufacturing value add are significant predictors of GDP growth rate. However, the residuals of the model are not normally distributed, which could impact the accuracy of the model's predictions.

b. ***Cluster Analysis***

Lastly a cluster analysis of the time series dataset was done as shown in the graph in Figure 18 below.

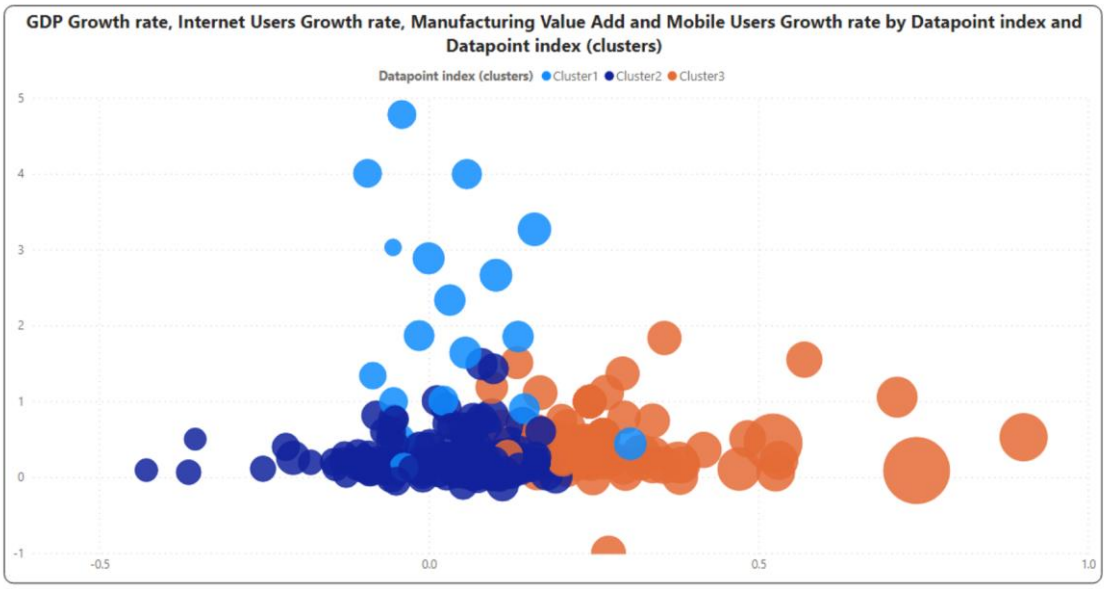


Figure 18 Cluster Analysis of the time series data.

The results of the cluster analysis revealed the presence of three distinct clusters. The first cluster is characterized by high levels of GDP growth rate, mobile users' growth rate, manufacturing value add, and Internet growth rate. The second cluster exhibits moderate levels of these variables, while the third cluster is distinguished by low levels of GDP growth rate, mobile users' growth rate, manufacturing value add, and Internet growth rate.

The cluster analysis was conducted using k-means clustering, a method that groups data points into clusters based on their similarity. The results of the cluster analysis suggest that there are three distinct groups of countries with respect to the variables of interest. Cluster 1 includes countries with high levels of economic growth, technological development, and mobile penetration. Cluster 2 includes

countries with moderate levels of these variables. Cluster 3 includes countries with low levels of these variables.

4.3 Prepositions

4.3.1 *Relationship between Internet Usage and GDP*

The results of this study suggest a weak positive correlation between Internet usage and GDP within SSA countries. Trend analysis revealed an overall upward trajectory, with significant variation in growth rates across different countries and years. Pooled Ordinary Least Squares (OLS) analysis determined that a 1% increase in Internet users corresponded to a 0.0135% increase in GDP. The Engle-Granger test provided strong evidence of cointegration between the variables, indicating a long-term relationship. Cluster analysis identified three distinct clusters, characterized by varying levels of GDP growth rate, mobile users' growth rate, manufacturing value add, and Internet growth rate.

In summary, this study provides empirical evidence supporting the existence of a relationship between Internet usage and GDP within SSA. Specifically, it suggests a weak positive association between Internet usage and GDP growth in the SSA context. However, further research is necessary to conclusively verify this relationship and to better understand the mechanisms through which Internet usage can drive economic growth.

4.3.2 *Relationship between Mobile Usage and GDP*

The results of the study showed that there is a weak positive correlation between the two variables. This means that as the number of mobile users increases, there is a slight increase in the GDP. However, the correlation is not strong, so it is not possible to say definitively that there is a causal relationship between the two variables.

The study also found that the growth rates of mobile users and GDP were generally aligned, but there were some outliers. This suggests that the relationship between the two variables may be stronger in some countries than in others.

The study also used several other statistical techniques to analyse the data, including trend analysis, stationarity, pooled OLS, ARIMA, co-integration, and cluster analysis. The results of these analyses provide further evidence that there is a weak positive relationship between mobile phone usage data and GDP.

In summary the study provides some evidence that there is a weak positive relationship between mobile phone usage data and GDP in SSA countries. However, the study was limited by the availability of data and the time that was analysed. More research is needed to confirm the findings of this study and to understand the mechanisms by which mobile phone usage data affects GDP.

4.3.3 *Manufacturing value Add effects on independent variables.*

The results of the study indicate that there is a strong positive correlation between manufacturing value add and GDP. This implies that an increase in manufacturing value add is associated with an increase in GDP.

Moreover, the study found that the relationship between digitalisation and GDP is weaker when manufacturing value add is included as a control variable. This suggests that some of the positive effect of digitalisation on GDP is since digitalisation is associated with an increase in manufacturing value add.

The study also employed several statistical techniques to analyse the data, including trend analysis, stationarity, pooled OLS, ARIMA, and cluster analysis. The results of these analyses provide further evidence that manufacturing value add has a strong positive correlation with GDP and that the relationship between digitalisation and GDP is weaker when manufacturing value add is included as a control variable.

Overall, the study provides evidence that manufacturing value add has a strong positive correlation with GDP and that the relationship between digitalisation and GDP is weaker when manufacturing value add is included as a control variable. Further research is needed to confirm these findings and to understand the mechanisms by which manufacturing value add affects GDP and the relationship between digitalisation and GDP.

4.4 Summary

In summary, the study has found a weak positive correlation between Internet usage and GDP within SSA countries. This suggests that there is a slight positive association between Internet usage and GDP growth in the SSA context. However, further research is necessary to conclusively verify this relationship and to better understand the mechanisms through which Internet usage can drive economic growth.

The study has also found a weak positive correlation between mobile phone usage data and GDP in SSA countries. However, the study was limited by the availability of data and the time that was analysed. More research is needed to confirm the findings of this study and to understand the mechanisms by which mobile phone usage data affects GDP.

The results of the study have also shown that there is a strong positive correlation between manufacturing value add and GDP. This implies that an increase in manufacturing value add is associated with an increase in GDP. The study has also found that the relationship between digitalisation and GDP is weaker when manufacturing value add is included as a control variable. This may suggest that some of the positive effect of digitalisation on GDP is because digitalisation is associated with an increase in manufacturing value add.

In conclusion, the study provides some evidence that there are weak positive relationships between Internet usage, mobile phone usage data, and manufacturing value add, and GDP in SSA countries. However, more research is needed to confirm these findings and to understand the mechanisms by which these factors affect GDP.

CHAPTER 5. DISCUSSION OF THE FINDINGS

5.1 Introduction

This chapter aims to provide a comprehensive analysis and interpretation of the findings obtained in the preceding section within the framework of the existing literature. The discussion begins by delving into the outcomes pertaining to the first objective, which aimed to determine the presence of a relationship between Internet usage data and GDP in the context of Sub-Saharan Africa (SSA). Subsequently, attention is directed towards the second objective, which sought to ascertain the existence of a relationship between Mobile phone usage data and GDP in SSA. Lastly, the chapter explores the last objective, which aimed to investigate the impact of manufacturing value add as a control variable on the relationship between Digitalisation and GDP.

5.2 Relationship between Internet Usage and GDP

The findings of this study are in accordance with the existing scholarly literature that has examined the relationship between Internet usage and GDP. The study uncovers a weak positive correlation between Internet usage and GDP within countries in the Sub-Saharan Africa (SSA) region. These findings are in consistent with previous studies conducted by Salahuddin and Gow (2016), Clarke et al. (2015), Fernández-Portillo et al. (2020), and Yu (2022), which have also provided evidence supporting a positive association between Internet access and economic growth.

The trend analysis performed in this study indicates an overall upward trajectory in Internet usage and GDP, although substantial variations in growth rates are

observed across different countries and years. This finding aligns with the notion that the adoption and utilization of the Internet may have differential effects depending on contextual factors such as infrastructure, socio-economic conditions, and policy frameworks. It is in line with the observations made by Myovella et al. (2020) and Hasbi and Dubus (2020), who discovered that the impact of digitalisation on economic growth can differ across countries and regions.

The utilization of Pooled Ordinary Least Squares (OLS) analysis in this study offers quantitative insights into the relationship between Internet users and GDP. The results indicate that a 1% increase in Internet users corresponds to a 0.0135% increase in GDP. Although the magnitude of this effect may appear small, it is consistent with the findings of previous studies that have reported similar positive associations between Internet usage and economic growth.

The strong evidence of cointegration between the variables, as revealed by the Engle-Granger test, further supports the notion of a long-term relationship between Internet usage and GDP. This finding is in line with the research conducted by Salahuddin and Gow (2016), Clarke et al. (2015), and Fernández-Portillo et al. (2020), who also employed co-integration tests and found evidence of a stable long-term association between Internet access and economic growth.

The cluster analysis employed in this study identifies three distinct clusters based on varying levels of GDP growth rate, mobile users' growth rate, manufacturing value add, and Internet growth rate. This analysis provides a nuanced understanding of the heterogeneity across countries in the Sub-Saharan Africa region and highlights the need to consider country-specific factors when examining the relationship between Internet usage and GDP.

In summary, the findings of this study contribute to the existing body of empirical evidence supporting a weak positive association between Internet usage and GDP growth in countries within the Sub-Saharan Africa region. The results are consistent with previous studies that have reported similar relationships between Internet access and economic growth. However, further research is warranted to validate these findings and to gain a deeper understanding of the mechanisms through which Internet usage drives economic growth in the Sub-Saharan Africa context. The discrepancies in growth rates and the presence. of distinct clusters underscore the importance of considering country-specific factors and contextual nuances in future investigations.

However, it is important to note that some previous research has also produced conflicting results. For instance, Harb (2017) found that Internet penetration has a significant role in high-income Arab and Middle Eastern (AME) countries but not in low-income AME countries. Similarly, Watanabe et al. (2018) observed that while the Internet has brought about additional services and benefits, productivity in developed countries has slowed. These conflicting findings may be attributable to differences in research methodologies and focal points. For example, Harb (2017) focused on the impact of Internet penetration on economic growth in the Arab and Middle Eastern region, while Watanabe et al. (2018) concentrated on productivity in developed countries. Additionally, discrepancies in how various studies measure Internet access and economic growth may lead to different conclusions.

5.3 Relationship between Mobile Usage and GDP

The study's findings suggest a weak positive correlation between mobile phone usage and GDP in SSA countries. This indicates that as the number of mobile phone users increases, there is a slight increase in GDP. However, the correlation observed is not strong, indicating that a definitive causal relationship cannot be established based on the results alone.

When compared to previous literature, both similarities and differences emerge. Miyajima (2022) and Myovella et al. (2020) reported a positive relationship between mobile phone usage and economic growth, aligning with the weak positive correlation found in the present study. These studies suggested that increased mobile phone usage stimulates consumption, enhances economic activity, and contributes to overall economic growth.

In contrast, Donou-Adonsou (2019) found a lesser impact of mobile phone usage on economic growth compared to the Internet, particularly in countries with a highly educated population. Although the present study did not specifically explore the differential impacts of mobile phone usage and the Internet, the weak positive correlation observed aligns with the notion that the relationship may vary depending on contextual factors, including education levels.

The study employed various statistical techniques to analyse the data, including trend analysis, stationarity, pooled OLS, ARIMA, co-integration, and cluster analysis. These methods aimed to strengthen the robustness of its findings. The consistent results across these analyses provide additional evidence supporting the existence of a weak positive relationship between mobile phone usage and GDP.

However, the study had certain limitations, including data availability and the analysed time. These constraints may have influenced the findings and limit their generalizability. Further research is necessary to replicate and validate the results of this study. Additionally, future investigations should delve into the mechanisms through which mobile phone usage affects GDP to gain a deeper understanding of the observed relationship.

In conclusion, this study contributes to existing literature by providing evidence of a weak positive relationship between mobile phone usage data and GDP in SSA countries. These findings are consistent with some previous studies, although the relationship may vary in strength across different countries. However, due to limitations of the study, cautious interpretation is warranted. Subsequent research should build upon these findings to enhance our understanding of the complex dynamics between mobile phone usage and economic growth.

5.4 Manufacturing value add effects.

The utilization of a manufacturing value-added control variable is essential in examining the relationship between GDP and digitalisation, as it can provide insight into the causal relationship between the two. The literature review indicates that the inclusion of a manufacturing value-added control variable can offer a more comprehensive understanding of the relationship between GDP and digitalisation.

The results of the study demonstrate a strong positive correlation between manufacturing value add and GDP, suggesting that an increase in manufacturing value add is associated with an increase in GDP. Furthermore, when manufacturing value add is included as a control variable, the relationship between digitalisation and GDP weakens. This indicates that some of the positive effects of digitalisation on GDP may be attributed to its association with an increase in manufacturing value add.

In conclusion, this study provides evidence of a strong positive correlation between manufacturing value add and GDP, and that the relationship between digitalisation and GDP weakens when manufacturing value add is included as a control variable. Further research is necessary to confirm these findings and to

understand the mechanisms by which manufacturing value add affects GDP and its relationship with digitalisation.

These findings are consistent with previous studies that have found a positive relationship between manufacturing value add and GDP. For instance, Hosseinzadeh (2018) found that the contribution of manufacturing value-added to GDP is higher in developed countries than in developing countries, with a strong positive relationship between the two variables. Wang (2016) found that financial development has a strong positive effect on economic growth, which is strengthened when accounting for manufacturing value-added. Salim (2015) found that manufacturing value-added has a positive and significant effect on economic growth in the USA, particularly in states with higher percentages of manufacturing activity. Singh (2013) found that manufacturing value-added has a positive and significant effect on India's economic growth.

These findings suggest that manufacturing value add is an important driver of economic growth due to its association with increased productivity, innovation, and exports.

5.5 Conclusion

In conclusion, this chapter provides a comprehensive analysis and interpretation of the findings regarding the relationships between Internet usage, mobile phone usage, manufacturing value add, and GDP in the context of Sub-Saharan Africa (SSA). The study confirms a weak positive correlation between Internet usage and GDP, aligning with previous research highlighting the positive association between Internet access and economic growth. However, the study acknowledges the variations in growth rates across countries and the need to consider contextual factors when examining this relationship.

Similarly, the study identifies a weak positive correlation between mobile phone usage and GDP in SSA countries, supporting previous studies that suggest increased mobile phone usage stimulates consumption and enhances economic activity. However, caution is warranted due to limitations in the data availability and analysed time, emphasizing the need for further research to replicate and validate the results.

Furthermore, the inclusion of manufacturing value add as a control variable reveals a strong positive correlation between manufacturing value add and GDP. The study demonstrates that when manufacturing value add is considered, the relationship between digitalisation and GDP weakens, indicating that some positive effects of digitalisation on GDP may be attributed to its association with increased manufacturing value add.

Overall, these findings contribute to the existing literature and provide valuable insights into the complex dynamics between digitalisation, mobile phone usage, manufacturing value add, and GDP in SSA. They emphasize the importance of considering country-specific factors and contextual nuances in future investigations. Further research is needed to validate these findings, explore the mechanisms through which Internet and mobile phone usage impact GDP, and understand the role of manufacturing value add in driving economic growth. By gaining a deeper understanding of these relationships, policymakers can make informed decisions to foster digitalisation, enhance mobile phone usage, and promote manufacturing value add for sustainable economic development in SSA.

CHAPTER 6. CONCLUSIONS and RECOMMENDATIONS

6.1 Introduction

This section provides a summary of the study's findings and subsequently integrates the results to draw conclusions, make recommendations, and suggest areas for further research.

6.2 Relationship between Internet Usage and GDP

In line with the study objectives, our investigation reveals a noteworthy positive and significant impact of Internet usage on economic growth in Sub-Saharan Africa (SSA). The study establishes a connection between Internet access and increased productivity, innovation, entrepreneurship, and access to information and communication—key factors contributing to economic development. The positive correlation found between GDP and Internet usage underscores the critical role of expanding Internet access in promoting economic growth in SSA. However, as some studies present conflicting results, further research is essential to discern the specific conditions influencing this relationship. Policymakers in developing African countries are urged to prioritize initiatives that expand Internet access, ensuring not only increased availability but also equitable access. These efforts should be accompanied by infrastructure development and initiatives promoting digital literacy.

6.3 Relationship between Mobile Usage and GDP

Aligned with our study objectives, findings in developing African countries indicate a positive correlation between mobile phone usage and economic growth (GDP), albeit with a complex causal relationship. This echoes previous research highlighting the association between mobile phone ownership and consumption in South Africa, as well as the positive impact of digitalization on economic growth in both SSA and OECD countries. Our study emphasizes the potential of mobile phone technology in promoting economic development, facilitating access to financial services, e-commerce, remote work, and education, thereby stimulating economic growth. Policymakers are encouraged to consider policies that foster the adoption and use of mobile phones and other digital technologies, recognizing their potential benefits in promoting economic development. However, as the study suggests, further research is needed to unravel the causal relationship between mobile phone usage and economic growth. This includes exploring specific mechanisms through which mobile phone usage may impact economic growth, such as fostering innovation and entrepreneurship, improving productivity, and enabling access to information and communication. Additionally, factors like government policies, infrastructure development, and education levels should be considered to comprehensively understand the intricate relationship between mobile phone usage and economic growth in developing African countries.

6.4 Manufacturing value add effects.

Addressing the study objectives, our findings indicate that the relationship between digitalization and economic growth in developing African countries is intricate and influenced by factors such as manufacturing value add. Considering the study objectives, we demonstrate that when manufacturing value add is considered, the connection between digitalization and GDP weakens, suggesting that some positive effects of digitalization on GDP may be attributed to increased manufacturing value add.

This nuanced understanding of the relationships between Internet usage, mobile phone usage, manufacturing value add, and GDP in SSA aligns with our study objectives. These findings contribute valuable insights to the existing literature and underscore the importance of tailored policies that consider country-specific factors and contextual nuances in fostering sustainable economic development in Sub-Saharan Africa. Future research endeavours should build upon these foundations to validate and expand upon our findings, exploring the intricate mechanisms through which these factors influence GDP.

6.5 Recommendations

Based on the findings of the study, several recommendations can be made to policymakers and other stakeholders to promote sustainable economic development in SSA and other developing African nations using digitalisation:

- Encourage investment in the manufacturing sector: The study highlights the importance of manufacturing value add in the relationship between digitalisation and economic growth. Therefore, policymakers should focus on promoting investment in the manufacturing sector to boost economic growth.

- Increase access to mobile phones and the internet: The study found that mobile phone usage and internet usage have a positive impact on economic growth. Policymakers should therefore prioritize increasing access to mobile phones and the internet in rural areas and among marginalized populations to promote economic growth.

- Foster innovation and entrepreneurship: Mobile phones and the internet can serve as platforms for innovation and entrepreneurship. Policymakers should therefore create an enabling environment for entrepreneurs and innovators to thrive, including through access to financing, training, and networking opportunities.

- Invest in digital infrastructure: Digital infrastructure, including broadband networks and data centres, is critical to the development of the digital economy. Policymakers should therefore prioritize investment in digital infrastructure to support economic growth.

- Provide digital skills training: Digitalisation requires a workforce with digital skills. Policymakers should therefore invest in digital skills training to equip the workforce with the skills needed to participate in the digital economy.

- Foster public-private partnerships: Public-private partnerships can be an effective way to promote digitalisation and economic growth. Policymakers should therefore foster partnerships between the public and private sectors to promote investment in digital infrastructure, innovation, and entrepreneurship.

In summary, the findings of this study suggest that digitalisation can be an effective tool for promoting sustainable economic development in SSA and other developing African nations. Policymakers and other stakeholders should therefore prioritize policies and investments that promote digitalisation, including investment in the manufacturing sector, increasing access to mobile phones and the internet, fostering innovation and entrepreneurship, investing in digital

infrastructure, providing digital skills training, and fostering public-private partnerships.

6.6 Suggestions for further research

In light of the study's findings, several suggestions for future research emerge. Firstly, there is a need for further exploration of the cause-and-effect relationship between mobile phone usage and economic growth, particularly in developing African countries. This may involve employing different statistical methods or examining other factors that could influence the connection between mobile phone usage and economic growth.

Secondly, future research could delve into the specific ways in which mobile phone usage influences economic growth in developing African countries. For example, it could investigate the role of mobile phones in facilitating financial transactions, fostering entrepreneurship and innovation, and supporting remote work and education.

Thirdly, research endeavours could focus on understanding the impact of digital infrastructure development, such as high-speed internet access and reliable electricity supply, on economic growth in developing African countries. This exploration may aid policymakers in identifying the most effective infrastructure investments for promoting economic development in these regions.

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APPENDIX (A) Raw data – Growth Rates

Year	Country	Population	% Internet Users	Number of Internet Users	Mobile users	Manufacturing Value Add	GDP
1999	Angola	0.03279062	2.899705393	3.027579151	1.443991853	-0.513071747	-0.0543
2000	Angola	0.032973168	0.459694222	0.507824965	0.07525	0.330604065	0.483782
2001	Angola	0.033397763	0.294808314	0.338052015	1.90630086	0.311689886	-0.0212
2002	Angola	0.033913706	0.98786162	1.055277374	0.866666667	0.617241768	0.710551
2003	Angola	0.034722435	0.370983528	0.418587414	1.5	0.272886607	0.165326
2004	Angola	0.035685875	0.25394418	0.298692275	1.114285714	0.547692315	0.322205
2005	Angola	0.036217009	1.459834056	1.548921888	1.177186486	0.311906292	0.569754
2006	Angola	0.036573055	0.311914921	0.359895658	0.895962928	0.308164903	0.416816
2007	Angola	0.037066333	0.133333333	0.175341844	0.624272741	0.172422984	0.245995
2008	Angola	0.037391192	0.117647059	0.159437214	0.365173204	0.381410545	0.356572
2009	Angola	0.037625391	0.210526316	0.256072842	0.197253031	0.172045804	-0.20592
2010	Angola	0.038054177	0.217391304	0.263718128	0.15956059	0.032936755	0.162037
2011	Angola	0.038303326	0.678571429	0.742866298	0.283925276	0.229206248	0.339501
2012	Angola	0.038302352	0.638297872	0.701048534	0.058964478	0.206733072	0.142198
2013	Angola	0.038061731	0.688311688	0.752571754	0.039114958	0.170005948	0.067228
2014	Angola	0.037531454	0.646153846	0.707936393	0.057760524	0.015109181	0.028807
2015	Angola	0.036839118	0.028037383	0.065909373	-0.011956969	-0.241470867	-0.3645
2016	Angola	0.036512912	0.054545455	0.09304998	-0.063625335	-0.321258504	-0.42856
2017	Angola	0.036147871	0.120689655	0.1612002	0.024830776	0.348594251	0.38387
2018	Angola	0.035251684	0.115384615	0.154703801	-0.002666701	0.038568054	0.127879
2019	Angola	0.034535753	0.107910068	0.146172576	0.116020782	-0.097591515	-0.10906

1999	Botswana	0.021657922	0.863196785	0.903549756	5.056616195	0.02424375	0.144829
2000	Botswana	0.020943414	1.586144575	1.640307273	1.415108696	0.067550306	0.055445
2001	Botswana	0.020234686	0.181977552	0.205894497	0.495404834	-0.015678563	-0.05161
2002	Botswana	0.018842973	-0.013105777	0.005490245	0	0.02755211	-0.00924
2003	Botswana	0.017677271	-0.012029862	0.005434755	0.339230251	0.300943461	0.381096
2004	Botswana	0.017637885	-0.012047423	0.005377971	0.174979437	0.160840996	0.192487
2005	Botswana	0.018139031	-0.012809875	0.005096797	0.078306939	-0.013210733	0.107334
2006	Botswana	0.018964955	0.314900206	0.33983723	0.459908262	0.435006477	2.53E-05
2007	Botswana	0.019843895	0.23078846	0.255212097	0.399347565	0.279246925	0.065339
2008	Botswana	0.020510153	0.183712121	0.207990238	0.290016766	-0.085337265	0.015472
2009	Botswana	0.020762509	-0.016	0.004430309	0.261349005	0.039625236	-0.05706
2010	Botswana	0.020823359	-0.024390244	-0.004074772	0.261090518	0.253354472	0.24893
2011	Botswana	0.020258034	0.5	0.530387051	0.22715135	0.087651027	0.195722
2012	Botswana	0.019394228	0.777777778	0.812256405	0.062567774	-0.03885818	-0.07963
2013	Botswana	0.019238999	0.875	0.911073124	0.053561219	0.015962576	0.02619
2014	Botswana	0.019437346	0.224824915	0.248632261	0.050425236	0.064373907	0.083964
2015	Botswana	0.019817499	0.015439021	0.035562483	0.019005972	-0.192975083	-0.12536
2016	Botswana	0.020495226	0.054967416	0.076589212	-0.053618264	0.000976086	0.11469
2017	Botswana	0.021009889	0.052099621	0.074204118	-0.01471487	0.013676273	0.0678
2018	Botswana	0.020637928	0.400499532	0.42940294	0.043399209	0.05306342	0.057542
2019	Botswana	0.019700099	0.117695266	0.139713973	0.108106286	-0.026769555	-0.01973
1999	Ghana	0.024690901	2.253536746	2.333869499	0.677148947	0.036085589	0.031866
2000	Ghana	0.025484504	0.464460799	0.501781856	0.857095936	-0.355015475	-0.35448
2001	Ghana	0.026954562	0.302006132	0.337101138	0.874712599	0.064963413	0.066603
2002	Ghana	0.027864963	3.151252875	3.266927381	0.586463328	0.163322781	0.160195
2003	Ghana	0.027516092	0.436927439	0.476466067	1.05682632	0.230661305	0.237755
2004	Ghana	0.027048436	0.438989414	0.477911827	1.130657713	0.133363796	0.163639
2005	Ghana	0.026955858	0.066635549	0.095387625	0.695905605	0.197813565	0.209799

2006	Ghana	0.026742957	0.487101217	0.526870701	0.811491846	1.14266059	0.902421
2007	Ghana	0.026397027	0.413790382	0.451110245	0.460284158	0.071081821	0.214616
2008	Ghana	0.026056971	0.109090909	0.137990458	0.52161354	0.01370617	0.155102
2009	Ghana	0.025679222	0.274004684	0.306720134	0.305821478	-0.184674593	-0.09173
2010	Ghana	0.025007533	0.433823529	0.469679918	0.15408339	0.166083959	0.23607
2011	Ghana	0.024681483	0.153846154	0.182324788	0.213850141	0.228473081	0.221759
2012	Ghana	0.024911183	0.177777778	0.207117616	0.210366485	-0.075490171	0.049155
2013	Ghana	0.024827466	0.41509434	0.450227546	0.093996989	2.116319883	0.52221
2014	Ghana	0.024368627	0.266666667	0.297533594	0.083288691	-0.170767722	-0.12798
2015	Ghana	0.023924402	0.210526316	0.239487434	0.153079643	-0.091725838	-0.09814
2016	Ghana	0.023669615	0.217391304	0.246206487	0.094168606	0.108333019	0.136796
2017	Ghana	0.022601074	0.353005451	0.383584828	-0.040551203	0.009096203	0.075513
2018	Ghana	0.021453689	0.135039245	0.159390024	0.113820777	0.110587249	0.114109
2019	Ghana	0.021109021	0.046735598	0.068831162	-0.001900531	0.019549838	0.015427
1999	Kenya	0.028408738	1.273236625	1.337816409	1.208720714	-0.150747694	-0.085
2000	Kenya	0.02958362	1.783745589	1.866098862	4.362798333	0.001823007	-0.01478
2001	Kenya	0.030751624	0.948634922	1.008558611	3.709428275	-0.030983279	0.022089
2002	Kenya	0.030800926	0.94870675	1.008728721	0.978536667	0.016975511	0.012455
2003	Kenya	0.030119107	1.435805988	1.509170289	0.340034975	0.120395177	0.133618
2004	Kenya	0.030346501	0.027745709	0.058934195	0.600566387	0.112348673	0.079897
2005	Kenya	0.030213237	0.025919938	0.056916301	0.81134549	0.226494669	0.164182
2006	Kenya	0.030193976	0.16057986	0.195622381	0.59157952	0.659925343	0.378251
2007	Kenya	0.030102434	0.222222222	0.259014086	0.546174641	0.247323223	0.237465
2008	Kenya	0.030236566	0.181818182	0.217552305	0.43651257	0.062188586	0.123191
2009	Kenya	0.030049561	0.173076923	0.20832737	0.187749397	0.120952383	0.179748
2010	Kenya	0.028575917	0.180327869	0.21405682	0.289411806	0.041193789	0.072221
2011	Kenya	0.026910059	0.222222222	0.255112294	0.124630285	0.114316103	0.03224
2012	Kenya	0.02558129	0.193181818	0.223704949	0.094405634	0.10694976	0.203272

2013	Kenya	0.024392049	0.238095238	0.268294918	0.03573662	0.076329353	0.093529
2014	Kenya	0.023206967	0.269230769	0.298685766	0.056632982	0.02158812	0.107251
2015	Kenya	0.022247077	0.005324536	0.027690069	0.121409265	0.017700006	0.026867
2016	Kenya	0.022265718	0.000732171	0.023014191	0.033573175	-0.002966908	0.066952
2017	Kenya	0.021995496	0.073921699	0.097543139	0.098324932	0.028010217	0.096514
2018	Kenya	0.020535347	0.093840264	0.116302654	0.156167324	0.081397211	0.123936
2019	Kenya	0.019981581	0.162506798	0.185735522	0.102099414	0.023456235	0.088682
1999	Mozambique	0.024504711	1.785090648	1.853338489	0.820520446	0.042894938	0.135362
2000	Mozambique	0.024836467	0.948289858	0.996678494	3.170954831	-0.095745937	-0.05353
2001	Mozambique	0.025450143	0.460245028	0.497408473	1.989366494	0.082175396	-0.04559
2002	Mozambique	0.026026968	0.622254905	0.664477282	0.668887404	-0.10585419	0.051576
2003	Mozambique	0.026307003	0.616018738	0.658531348	0.71046754	0.275371731	0.110338
2004	Mozambique	0.026458723	0.619511148	0.662361344	0.624758753	0.275304144	0.210637
2005	Mozambique	0.026236022	0.257428568	0.290418491	1.124213277	0.011607705	0.119373
2006	Mozambique	0.025969276	-0.013346445	0.012276234	0.555455892	0.137596593	0.074317
2007	Mozambique	0.026260198	0.079536337	0.107885175	0.316530851	0.094424781	0.138822
2008	Mozambique	0.026552837	0.714285714	0.759804864	0.430297524	0.033823196	0.201453
2009	Mozambique	0.027057613	0.717948718	0.764432309	0.355453545	-0.15541047	-0.05111
2010	Mozambique	0.028393843	0.555970149	0.600150121	0.209921449	-0.113137616	-0.06797
2011	Mozambique	0.02976104	0.103117506	0.135947431	0.087368995	0.272967321	0.295093
2012	Mozambique	0.030605097	0.086956522	0.120222932	0.120891062	0.002603665	0.136929
2013	Mozambique	0.031204351	0.1	0.134324786	0.408439491	-0.017375099	0.038134
2014	Mozambique	0.031165111	0.090909091	0.124907394	0.490380275	0.023115701	0.043699
2015	Mozambique	0.030897928	0.083333333	0.116806089	0.089397087	-0.080971661	-0.09963
2016	Mozambique	0.031786282	0.076923077	0.111154458	-0.253754718	-0.225438553	-0.25164
2017	Mozambique	0.031518359	0.113760944	0.148864861	-0.209648361	0.07108353	0.107404
2018	Mozambique	0.029907376	0.398094327	0.439907659	0.185149332	0.193566366	0.123028
2019	Mozambique	0.029286316	0.342986484	0.382317611	0.049673418	0.050485611	0.036687

1999	Nigeria	0.025752202	0.626490158	0.668375861	0.25	0.012982777	0.08733
2000	Nigeria	0.026370392	0.561471784	0.602648407	0.2	0.002501801	0.16971
2001	Nigeria	0.026867242	0.402937522	0.440630584	7.882033333	0.047610854	0.048216
2002	Nigeria	0.027192035	2.564595022	2.661523614	4.888478989	0.107556299	0.305737
2003	Nigeria	0.027293505	0.74303439	0.790607909	1.007248335	0.12509736	0.101888
2004	Nigeria	0.027321608	1.302528352	1.365437129	1.904361777	0.167352492	0.29622
2005	Nigeria	0.027303013	1.759545794	1.834889709	1.031985931	0.198572082	0.293934
2006	Nigeria	0.027325947	0.562353563	0.605046354	0.738968204	0.194392005	0.357399
2007	Nigeria	0.027466712	0.220911803	0.254446235	0.249779053	0.107419312	0.166932
2008	Nigeria	0.027570079	0.1816839	0.214263017	0.559290488	0.186235638	0.219993
2009	Nigeria	0.027649184	0.1625	0.194642177	0.18304569	-0.166147213	-0.13099
2010	Nigeria	0.027823838	0.23655914	0.270964961	0.171495206	0.039967787	0.243999
2011	Nigeria	0.02802617	0.2	0.233631404	0.090145685	0.235922989	0.129366
2012	Nigeria	0.027874306	0.166666667	0.19918669	0.185047548	0.205839578	0.119441
2013	Nigeria	0.027341852	0.186335404	0.218772011	0.128290399	0.295796291	0.121012
2014	Nigeria	0.026629636	0.09947644	0.128755097	0.092059629	0.19134812	0.103951
2015	Nigeria	0.025737509	0.166666667	0.19669376	0.085418406	-0.159822638	-0.14134
2016	Nigeria	0.025387245	0.163265306	0.192797407	0.023285003	-0.244433147	-0.17926
2017	Nigeria	0.025595243	0.164912281	0.194728494	-0.061046169	-0.064763586	-0.07143
2018	Nigeria	0.025280721	0.165662651	0.195131443	0.191901741	0.238851889	0.122406
2019	Nigeria	0.024784152	0.16360138	0.192440254	0.068671398	0.268854459	0.062552
1999	Rwanda	0.011995737	4.710550867	4.779053134	1.2	-0.012429545	0.083628
2000	Rwanda	0.012535228	-0.064680702	-0.052956261	2.545454545	-0.098228515	-0.04088
2001	Rwanda	0.014050821	2.830444335	2.884265221	0.666666667	-0.105190117	-0.04937
2002	Rwanda	0.018040621	0.216527973	0.238474892	0.267553846	0.076603516	-0.00034
2003	Rwanda	0.023373011	0.219047457	0.247540266	0.586581059	-0.009346241	0.087704
2004	Rwanda	0.026127592	0.207150324	0.238690255	0.050114749	0.105666993	0.111466
2005	Rwanda	0.026666278	0.290555156	0.32496946	0.624363485	0.21578375	0.234474

2006	Rwanda	0.027006307	-1	-1	0.40911211	0.167893502	0.131556
2008	Rwanda	0.027178771	1.12727015	1.185086738	1.08244363	0.241324919	0.272602
2009	Rwanda	0.026757423	0.711111111	0.756896034	0.836673252	0.101503856	0.095488
2010	Rwanda	0.026413874	0.038961039	0.066404025	0.460845149	0.116589808	0.079332
2011	Rwanda	0.025987021	-0.125	-0.102261357	0.252886289	0.139343994	0.124128
2012	Rwanda	0.024903441	0.146264897	0.174810837	0.279915136	0.100471791	0.111793
2013	Rwanda	0.024078225	0.121655465	0.148662938	0.175443803	-0.158014149	0.021606
2014	Rwanda	0.024060227	0.177777778	0.206115378	0.158145614	0.052235841	0.053581
2015	Rwanda	0.024146473	0.179245283	0.207719898	0.130708341	0.039514486	0.036997
2016	Rwanda	0.024730827	0.168	0.196885605	0.018484137	-0.001394841	0.017736
2017	Rwanda	0.025097857	0.178082192	0.20764953	-0.011468433	0.220049856	0.06466
2018	Rwanda	0.024649276	0.11627907	0.143794541	0.099939938	0.0353024	0.042107
2019	Rwanda	0.02419603	0.112396358	0.139311933	-0.004335913	0.178072384	0.074036
1999	Uganda	0.032904439	0.616553911	0.669745711	0.8786	-0.021695619	-0.08903
2000	Uganda	0.031850257	0.551146025	0.600550425	1.251907449	-0.175845667	0.032455
2001	Uganda	0.030916172	0.453418739	0.498352883	1.233971303	-0.061869809	-0.05696
2002	Uganda	0.031569468	0.614210698	0.665170471	0.387238995	0.101646684	0.057882
2003	Uganda	0.03169478	0.210251759	0.248610422	0.973428085	0.025926261	0.069324
2004	Uganda	0.030026785	0.548824197	0.595330408	0.501006868	0.0840531	0.201699
2005	Uganda	0.029488747	1.419828406	1.491186113	0.128978958	0.281517785	0.163705
2006	Uganda	0.029579246	0.451816697	0.49476034	0.527269824	0.092448878	0.079923
2007	Uganda	0.029769932	0.451735198	0.494953256	1.088431107	0.198846124	0.192923
2008	Uganda	0.029701783	0.056654851	0.088039384	1.039164985	0.244058521	0.213218
2009	Uganda	0.029585778	0.056701031	0.087964353	0.096888741	2.919964623	0.740104
2010	Uganda	0.029580817	0.048780488	0.079804271	0.367074557	0.07969738	0.061511
2011	Uganda	0.029497805	0.069767442	0.101323234	0.301578452	0.065563632	0.044924
2012	Uganda	0.029359824	0.043478261	0.074114599	-0.020399183	-0.044364256	-0.0203
2013	Uganda	0.029185259	0.0625	0.093509338	0.104684549	-0.011261653	0.058957

2014	Uganda	0.030134999	0.058823529	0.090731176	0.127142496	0.121009554	0.127841
2015	Uganda	0.031395863	0.074074074	0.107795557	-0.00715253	0.07817865	-0.00691
2016	Uganda	0.033912291	0.017241379	0.051738365	0.129484552	-0.127831973	-0.09829
2017	Uganda	0.035583136	0	0.035583136	0.092405074	0.006905411	0.052749
2018	Uganda	0.034597828	0.016949153	0.052133385	-0.019112884	0.088677258	0.07099
2019	Uganda	0.034533816	0.002969182	0.037605535	0.037735729	0.052378321	0.073679
1999	South Africa	0.011177553	0.41635814	0.432189558	0.554689841	-0.050663436	-0.00958
2000	South Africa	0.009675145	0.299376927	0.311948586	0.607363146	0.025465813	0.001563
2001	South Africa	0.00889594	0.186603429	0.197159382	0.293560379	-0.104335867	-0.10757
2002	South Africa	0.00914255	0.057306591	0.066973069	0.270232687	-0.045061201	-0.04682
2003	South Africa	0.009284934	0.044315201	0.054011599	0.230477303	0.480626247	0.526246
2004	South Africa	0.009396777	0.20226731	0.213564748	0.236002372	0.262427175	0.298377
2005	South Africa	0.009495744	-0.111164743	-0.102724591	0.629634723	0.090375283	0.129246
2006	South Africa	0.00968251	0.015837146	0.025672999	0.16790486	-0.055590631	0.0519
2007	South Africa	0.010190344	0.060237556	0.071041741	0.066512027	0.085348734	0.096145
2008	South Africa	0.01139525	0.045208663	0.057119077	0.063829787	-0.040619115	-0.05087
2009	South Africa	0.011963953	0.18623962	0.200431736	0.031911111	-0.030483119	0.043086
2010	South Africa	0.012001811	1.4	1.428804346	0.084761823	0.209136875	0.26569
2011	South Africa	0.012714203	0.415416667	0.433412562	0.270547129	0.018805506	0.097843
2012	South Africa	0.013380311	0.206947306	0.223096637	0.06865625	-0.07989398	-0.05194
2013	South Africa	0.013709334	0.134146341	0.149694732	0.123859958	-0.085713601	-0.07715
2014	South Africa	0.015887833	0.053763441	0.070505458	0.031424501	-0.040348484	-0.04911
2015	South Africa	0.020956741	0.05957379	0.081779003	0.109973267	-0.087761953	-0.09048
2016	South Africa	0.009767433	0.040079347	0.050238253	-0.063484594	-0.069253682	-0.0667
2017	South Africa	0.003880294	0.040136935	0.044172972	0.07383227	0.181563333	0.178819
2018	South Africa	0.012330704	0.110964833	0.124663812	0.044411911	0.057780722	0.059538
2019	South Africa	0.013034963	0.116937101	0.131496334	0.049168034	-0.04581407	-0.03867
1999	Zambia	0.026546797	3.86509236	3.994244982	2.41283293	-0.087923335	-0.0377

2000	Zambia	0.028052315	0.299337106	0.33578652	2.506669032	-0.020841288	0.057683
2001	Zambia	0.030413898	0.220115933	0.257224415	0.226062942	0.092460724	0.13714
2002	Zambia	0.031037198	1.0492936	1.11289793	0.147623762	0.081111264	0.024268
2003	Zambia	0.031373218	1.052289226	1.116676143	0.732666149	0.237374089	0.168817
2004	Zambia	0.032300044	0.121896	0.15813329	0.926780083	0.258763954	0.269131
2005	Zambia	0.033681503	0.181818182	0.221623594	1.044903242	0.309387596	0.339297
2006	Zambia	0.035166586	0.230769231	0.274051183	0.751684729	0.463792047	0.531092
2007	Zambia	0.035960706	0.1875	0.230203338	0.586593865	0.016632438	0.101914
2008	Zambia	0.036356261	0.157894737	0.19999146	0.341026197	0.241011284	0.274163
2009	Zambia	0.036187834	0.136363636	0.177486175	0.245176113	-0.120806659	-0.14419
2010	Zambia	0.035590622	0.2	0.242708746	0.236075351	0.153634054	0.322097
2011	Zambia	0.034347814	0.166666667	0.206739116	0.498910683	0.148115428	0.157605
2012	Zambia	0.033565838	0.171428571	0.210748553	0.289069469	0.023419384	0.087109
2013	Zambia	0.033253942	0.170731707	0.209663151	-0.012245033	-0.064093609	0.099368
2014	Zambia	0.033004122	0.354166667	0.398859748	-0.027023795	0.095994721	-0.03197
2015	Zambia	0.032433836	0.353846154	0.397756578	0.142647254	-0.136374281	-0.21701
2016	Zambia	0.031974621	0.170454545	0.207879386	0.039740433	0.007698788	-0.01378
2017	Zambia	0.031625749	0.184466019	0.221925644	0.118290836	0.305371212	0.234521
2018	Zambia	0.031092457	0.17213091	0.20857534	0.151186896	-0.143167032	0.016928
2019	Zambia	0.030533038	0.174825413	0.210696402	0.113141981	-0.121740717	-0.11413
1999	Namibia	0.024380844	0.172531688	0.201119001	0.538461538	-0.080787361	-0.00118
2000	Namibia	0.022979547	3.891888523	4.004301906	1.733333333	0.125485034	0.013883
2001	Namibia	0.020482744	0.469521084	0.499620909	0.3	-0.103914566	-0.09304
2002	Namibia	0.017303903	0.089665772	0.108521242	0.407129456	-0.078209449	-0.05851
2003	Namibia	0.014243921	0.275711046	0.293882172	0.49114	0.778973837	0.470946
2004	Namibia	0.012519937	0.1324098	0.1465875	0.279088483	0.247091213	0.341569
2005	Namibia	0.012095972	0.05396751	0.066716271	0.568908929	0.085951638	0.096713
2006	Namibia	0.012070621	0.096962464	0.110203482	0.35643646	0.325507709	0.103938

2007	Namibia	0.012551358	0.099284604	0.113082118	0.314404628	0.181858404	0.104695
2008	Namibia	0.013452701	0.102033232	0.116858555	0.314556337	-0.185268432	-0.02625
2009	Namibia	0.014405814	0.219740176	0.237311526	0.550927757	0.185191196	0.038501
2010	Namibia	0.015161135	0.784615385	0.81167218	0.195207578	0.222627212	0.278835
2011	Namibia	0.015752611	0.034482759	0.050778563	0.1253405	0.198667313	0.095533
2012	Namibia	0.016474859	0.07845	0.096217311	-0.021718892	-0.056657706	0.041411
2013	Namibia	0.017089049	0.074072357	0.092427232	0.270668468	-0.21836732	-0.07658
2014	Namibia	0.017460116	0.067625899	0.086266771	-0.020869434	-0.008437653	0.032561
2015	Namibia	0.017700839	0.730987319	0.761627248	-0.045363823	0.050307195	-0.08848
2016	Namibia	0.017806952	0.208094245	0.229606721	0.043192904	-0.032422086	-0.0541
2017	Namibia	0.017725252	0.187026579	0.208066925	0.007611042	0.258420756	0.202682
2018	Namibia	0.017401315	0.085852774	0.10474804	0.029511648	0.067864815	0.061024
2019	Namibia	0.017028034	0.12067037	0.139753183	0.02332554	-0.071139663	-0.08333

APPENDIX (B) Detailed Data analysis in Python Language

The relationship between GDP and digitalisation in SSA

Import Libraries

This part of the code loadas almost all Libraries that will be used in this time series analysis to investigate the relationship between GDP and digilisatlisation.

In [1]:
```
#!conda install -c conda-forge fable
from dateutil.parser import parse
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import statsmodels
from statsmodels.tsa.stattools import grangercausalitytests
print("Statsmodels Version: ", statsmodels.__version__)

warnings.filterwarnings('ignore')
plt.rcParams.update({'figure.figsize': (10, 7), 'figure.dpi': 120})
```

```
Statsmodels Version:  0.13.2
```

In [2]:
```
import pandas as pd

df = pd.read_excel('C:\\Users\\Bright.Sikazwe\\Downloads\\THESIS MAY2023\\RateOfChangeDateSetV2.xlsx')

print(df)
```

```
      Internet Users  Mobile users  Manufacturing Value Add       GDP
0           3.027579      1.443992                -0.513072 -0.054303
1           0.507825      0.075250                 0.330604  0.483782
2           0.338052      1.906301                 0.311690 -0.021198
3           1.055277      0.866667                 0.617242  0.710551
4           0.418587      1.500000                 0.272887  0.165326
..               ...           ...                      ...       ...
225         0.761627     -0.045364                 0.050307 -0.088476
226         0.229607      0.043193                -0.032422 -0.054096
227         0.208067      0.007611                 0.258421  0.202682
228         0.104748      0.029512                 0.067865  0.061024
229         0.139753      0.023326                -0.071140 -0.083331

[230 rows x 4 columns]
```

Summary Stats for Growth Rates

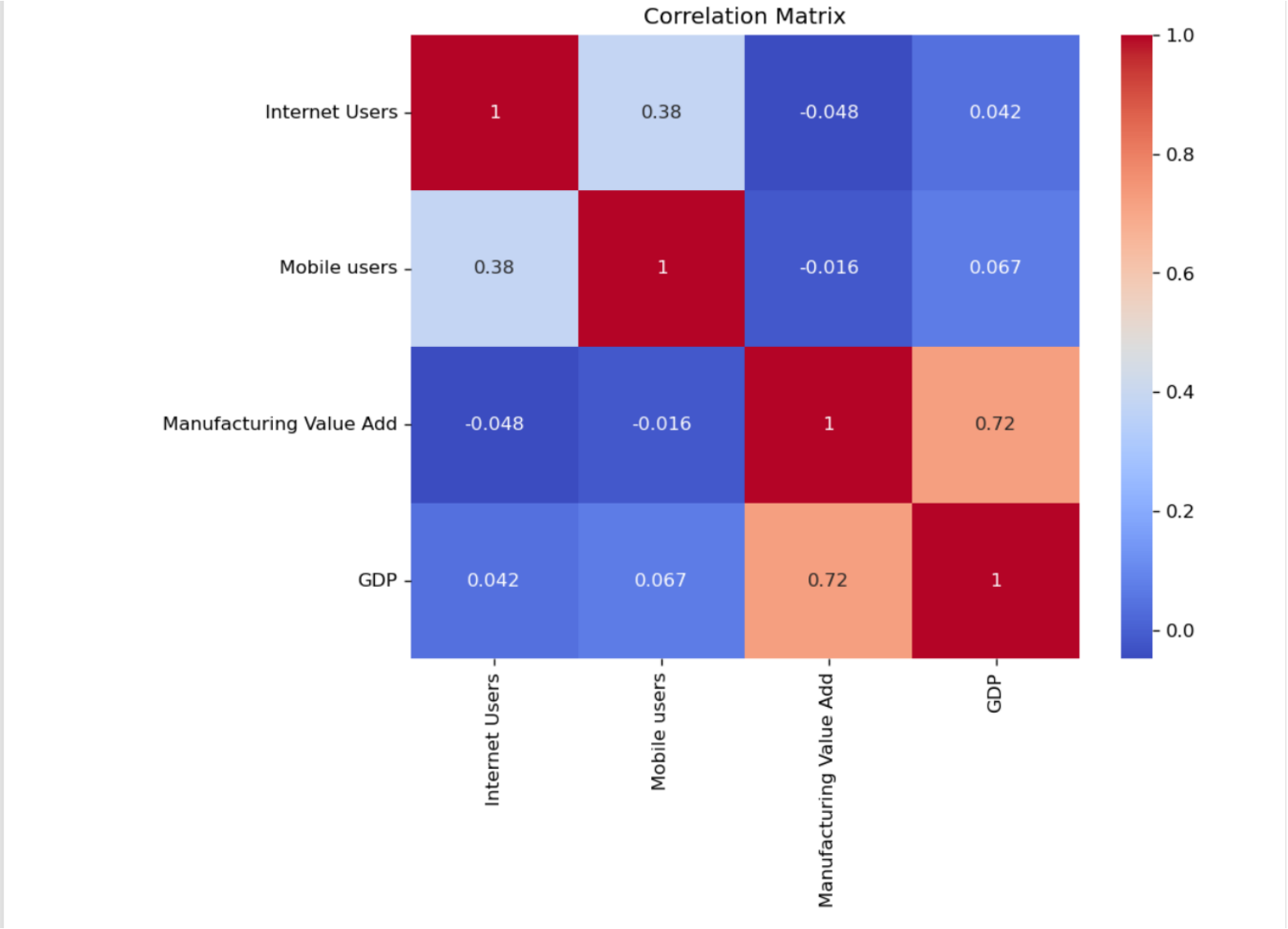
In [3]:
```
import pandas as pd

df = pd.read_excel('C:\\Users\\Bright.Sikazwe\\Downloads\\THESIS MAY2023\\RateOfChangeDateSetV2.xlsx')

# Get the summary statistics for all variables
summary_stats = df.describe()

# Get the names of the variables
variable_names = df.columns

# Create a new dataframe with the summary statistics and the variable names
summary_stats_with_names = pd.DataFrame(summary_stats)
summary_stats_with_names.columns = ['Variable'] + variable_names

# Print the summary statistics table
print(summary_stats_with_names)
```

```
       Variable Internet Users  VariableMobile users  \
count                230.000000            230.000000
mean                   0.443683              0.509726
std                    0.685520              0.885782
min                   -1.000000             -0.253755
25%                    0.116819              0.085906
50%                    0.214160              0.240626
75%                    0.490548              0.590333
max                    4.779053              7.882033

       VariableManufacturing Value Add  VariableGDP
count                       230.000000   230.000000
mean                          0.100220     0.094619
std                           0.293387     0.171335
min                          -0.513072    -0.428561
25%                          -0.025501    -0.005473
50%                           0.064669     0.077422
75%                           0.185975     0.164063
max                           2.919965     0.902421
```

In [20]:
```
import pandas as pd

file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'
df = pd.read_excel(file_path)

# Calculate correlation matrix
correlation_matrix = df[[' Internet Users', 'Mobile users', 'Manufacturing Value Add', 'GDP']].corr()

# Display correlation matrix
print(correlation_matrix)
```

```
                        Internet Users  Mobile users  \
 Internet Users               1.000000      0.384546
Mobile users                  0.384546      1.000000
Manufacturing Value Add      -0.047747     -0.016386
GDP                           0.041748      0.067496

                        Manufacturing Value Add       GDP
 Internet Users                       -0.047747  0.041748
Mobile users                          -0.016386  0.067496
Manufacturing Value Add                1.000000  0.724709
GDP                                    0.724709  1.000000
```

In [43]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'
df = pd.read_excel(file_path)

# Calculate correlation matrix
correlation_matrix = df[[' Internet Users', 'Mobile users', 'Manufacturing Value Add', 'GDP']].corr()

# Create heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```


Correlation Matrix
Internet Users
Mobile users
Manufacturing Value Add
GDP
1
0.38
-0.048
0.042
0.38
1
-0.016
0.067
-0.048
-0.016
1
0.72
0.042
0.067
0.72
1
Internet Users
Mobile users
Manufacturing Value Add
GDP
1.0
0.8
0.6
0.4
0.2
0.0

In [44]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'
df = pd.read_excel(file_path)
correlation_matrix = df[[' Internet Users', 'Mobile users', 'Manufacturing Value Add', 'GDP']].corr()
sns.set(style="ticks")
sns.pairplot(df[[' Internet Users', 'Mobile users', 'Manufacturing Value Add', 'GDP']])
plt.suptitle('Scatter Matrix')
plt.show()
```

In [4]:
```
import pandas as pd
from statsmodels.tsa.stattools import adfuller

df = pd.read_excel('C:\\Users\\Bright.Sikazwe\\Downloads\\THESIS MAY2023\\RateOfChangeDateSetV2.xlsx')

# Get the names of the variables
variable_names = df.columns

# Create a new dataframe to store the results of the Augmented Dickey-Fuller test
adf_results = pd.DataFrame()

# Loop over the variables
for variable in variable_names:

    # Perform the Augmented Dickey-Fuller test
    adf_test = adfuller(df[variable])

    # Store the results of the test in the dataframe
    adf_results = adf_results.append({
        'Variable': variable,
        'Test Statistic': adf_test[0],
        'P-value': adf_test[1],
        'Critical Values (1%)': adf_test[4]['1%'],
        'Critical Values (5%)': adf_test[4]['5%'],
        'Critical Values (10%)': adf_test[4]['10%']
    }, ignore_index=True)

    # Add a column to show if the variable is stationary or not
    adf_results['Stationary'] = adf_results['P-value'] < 0.05

# Print the dataframe
print(adf_results)
```

```
                 Variable  Test Statistic       P-value  \
0          Internet Users       -9.252825  1.476456e-15
1            Mobile users       -8.791299  2.236822e-14
2  Manufacturing Value Add      -14.230428  1.600077e-26
3                     GDP       -7.852376  5.556952e-12

   Critical Values (1%)  Critical Values (5%)  Critical Values (10%)  \
0            -3.459361             -2.874302              -2.573571
1            -3.459361             -2.874302              -2.573571
2            -3.459233             -2.874245              -2.573541
3            -3.460849             -2.874953              -2.573919

   Stationary
0        True
1        True
2        True
3        True
```

In [5]:
```
import pandas as pd

file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'
df = pd.read_excel(file_path)
import statsmodels.api as sm


#df.columns

X = df[[' Internet Users', 'Mobile users', 'Manufacturing Value Add']]
y = df['GDP']
X = sm.add_constant(X)
model = sm.OLS(y, X)
results = model.fit()
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    GDP   R-squared:                       0.534
Model:                            OLS   Adj. R-squared:                  0.528
Method:                 Least Squares   F-statistic:                     86.32
Date:                Sat, 03 Jun 2023   Prob (F-statistic):          2.99e-37
Time:                        12:57:03   Log-Likelihood:                167.70
No. Observations:                 230   AIC:                            -327.4
Df Residuals:                     226   BIC:                            -313.7
Df Model:                           3
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                      0.0402      0.010      3.991      0.000       0.020       0.060
 Internet Users            0.0135      0.012      1.096      0.274      -0.011       0.038
Mobile users               0.0114      0.010      1.193      0.234      -0.007       0.030
Manufacturing Value Add    0.4253      0.027     16.019      0.000       0.373       0.478
==============================================================================
Omnibus:                       26.743   Durbin-Watson:                   1.712
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              107.145
Skew:                          -0.299   Prob(JB):                     5.42e-24
Kurtosis:                       6.290   Cond. No.                         4.72
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [6]:

```
import pandas as pd
from statsmodels.tsa.vector_ar.var_model import VAR
from statsmodels.tsa.arima.model import ARIMA

# Path to the Excel file
file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetv2.xlsx'

# Load the dataset into a pandas dataframe
df = pd.read_excel(file_path)

# Select the columns for the VAR model
var_df = df[["GDP", " Internet Users", "Mobile users", "Manufacturing Value Add"]]

# Fit the VAR model
var_model = VAR(var_df)
var_results = var_model.fit()

# Select the column for the ARIMA model
arima_df = df[["GDP"]]

# Fit the ARIMA model
arima_model = ARIMA(arima_df, order=(1, 1, 1))
arima_results = arima_model.fit()

# Compare the models based on AIC and BIC
var_aic = var_results.aic
var_bic = var_results.bic
arima_aic = arima_results.aic
arima_bic = arima_results.bic

# Print the AIC and BIC values
print("VAR Model:")
print("AIC:", var_aic)
print("BIC:", var_bic)
print()
print("ARIMA Model:")
print("AIC:", arima_aic)
print("BIC:", arima_bic)
print()

# Determine the best fitting model
if var_aic < arima_aic and var_bic < arima_bic:
    print("VAR model fits the best.")
elif arima_aic < var_aic and arima_bic < var_bic:
    print("ARIMA model fits the best.")
else:
    print("Both models have similar performance.")
```

```
VAR Model:
AIC: -8.214249996046421
BIC: -7.91436161145653

ARIMA Model:
AIC: -158.88868210523685
BIC: -148.58751609457414

ARIMA model fits the best.
```

Model	AIC	BIC
VAR	-8.214249996046421	-7.91436161145653
ARIMA	-158.88868210523685	-148.58751609457414

```python
# Path to the Excel file
file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'

# Load the dataset into a pandas dataframe
df = pd.read_excel(file_path)

# Select the columns for the VAR model
var_df = df[["GDP", " Internet Users", "Mobile users", "Manufacturing Value Add"]]

# Fit the VAR model
var_model = VAR(var_df)
var_results = var_model.fit()

# Select the column for the ARIMA model
arima_df = df[["GDP"]]

# Fit the ARIMA model
arima_model = ARIMA(arima_df, order=(1, 1, 1))
arima_results = arima_model.fit()

# Compare the models based on AIC and BIC
var_aic = var_results.aic
var_bic = var_results.bic
arima_aic = arima_results.aic
arima_bic = arima_results.bic

# Print the AIC and BIC values
print("VAR Model:")
print("AIC:", var_aic)
print("BIC:", var_bic)
print()
print(var_results.summary())
print()

print("ARIMA Model:")
print("AIC:", arima_aic)
print("BIC:", arima_bic)
print()
print(arima_results.summary())
print()

# Determine the best fitting model
if var_aic < arima_aic and var_bic < arima_bic:
    print("VAR model fits the best.")
elif arima_aic < var_aic and arima_bic < var_bic:
    print("ARIMA model fits the best.")
else:
    print("Both models have similar performance.")
```

```
VAR Model:
AIC: -8.214249996046421
BIC: -7.91436161145653

  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sat, 03, Jun, 2023
Time:                     13:00:06
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                   -7.91436
Nobs:                     229.000    HQIC:                  -8.09327
Log likelihood:          -339.216    FPE:                0.000270775
AIC:                     -8.21425    Det(Omega_mle):     0.000248363
--------------------------------------------------------------------
Results for equation GDP
=================================================================================================
                              coefficient       std. error           t-stat            prob
-------------------------------------------------------------------------------------------------
const                           0.069496         0.014688            4.731           0.000
L1.GDP                          0.292800         0.093402            3.135           0.002
L1. Internet Users             -0.032593         0.017303           -1.884           0.060
L1.Mobile users                 0.036163         0.013386            2.701           0.007
L1.Manufacturing Value Add     -0.061055         0.054400           -1.122           0.262
=================================================================================================
```

```
--------------------------------------------------------------------
Results for equation GDP
==============================================================================
                              coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const                            0.069496         0.014688            4.731           0.000
L1.GDP                           0.292800         0.093402            3.135           0.002
L1. Internet Users              -0.032593         0.017303           -1.884           0.060
L1.Mobile users                  0.036163         0.013386            2.701           0.007
L1.Manufacturing Value Add      -0.061055         0.054400           -1.122           0.262
==============================================================================

Results for equation  Internet Users
==============================================================================
                              coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const                            0.353493         0.056502            6.256           0.000
L1.GDP                          -0.359790         0.359299           -1.001           0.317
L1. Internet Users              -0.047942         0.066563           -0.720           0.471
L1.Mobile users                  0.252226         0.051495            4.898           0.000
L1.Manufacturing Value Add       0.054092         0.209265            0.258           0.796
==============================================================================

Results for equation Mobile users
==============================================================================
                              coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const                            0.208541         0.069595            2.997           0.003
L1.GDP                           0.158437         0.442553            0.358           0.720
L1. Internet Users               0.186921         0.081986            2.280           0.023
L1.Mobile users                  0.404538         0.063427            6.378           0.000
L1.Manufacturing Value Add      -0.081737         0.257755           -0.317           0.751
==============================================================================

Results for equation Manufacturing Value Add
==============================================================================
                              coefficient       std. error           t-stat            prob
------------------------------------------------------------------------------
const                            0.083166         0.025609            3.247           0.001
L1.GDP                           0.360100         0.162850            2.211           0.027
L1. Internet Users              -0.050216         0.030169           -1.664           0.096
L1.Mobile users                  0.032866         0.023340            1.408           0.159
L1.Manufacturing Value Add      -0.090084         0.094848           -0.950           0.342
==============================================================================
```

Correlation matrix of residuals

	GDP	Internet Users	Mobile users	Manufacturing Value Add
GDP	1.000000	0.023189	0.011979	0.713036
Internet Users	0.023189	1.000000	0.294155	-0.030797
Mobile users	0.011979	0.294155	1.000000	-0.032885
Manufacturing Value Add	0.713036	-0.030797	-0.032885	1.000000

ARIMA Model:
AIC: -158.88868210523685
BIC: -148.58751609457414

SARIMAX Results

Dep. Variable:	GDP	No. Observations:	230
Model:	ARIMA(1, 1, 1)	Log Likelihood	82.444
Date:	Sat, 03 Jun 2023	AIC	-158.889
Time:	13:00:06	BIC	-148.588
Sample:	0	HQIC	-154.733
	- 230		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.2290	0.052	4.409	0.000	0.127	0.331
ma.L1	-0.9982	0.107	-9.368	0.000	-1.207	-0.789
sigma2	0.0279	0.004	7.469	0.000	0.021	0.035

Ljung-Box (L1) (Q):	0.12	Jarque-Bera (JB):	162.81
Prob(Q):	0.72	Prob(JB):	0.00
Heteroskedasticity (H):	0.57	Skew:	0.89
Prob(H) (two-sided):	0.02	Kurtosis:	6.73

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

ARIMA model fits the best.

```
GDP
{'Mean Absolute Error (MAE)': 0.11742884236907965, 'Root Mean Squared Error (RMSE)': 0.150442758672959}

 Internet Users
{'Mean Absolute Error (MAE)': 0.44548384787146944, 'Root Mean Squared Error (RMSE)': 0.854741678432694}

Mobile users
{'Mean Absolute Error (MAE)': 0.3628860665397041, 'Root Mean Squared Error (RMSE)': 0.4492667573496254}

Manufacturing Value Add
{'Mean Absolute Error (MAE)': 0.16431086344749662, 'Root Mean Squared Error (RMSE)': 0.21694563537484662}
```

Variable	MAE	RMSE
GDP	0.1174	0.1504
Internet Users	0.4455	0.8547
Mobile Users	0.3629	0.4493
Manufacturing Value Add	0.1643	0.2169

In [15]:

```
import pandas as pd
from statsmodels.tsa.arima.model import ARIMA

# Path to the Excel file
file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSet.xlsx'

# Load the dataset into a pandas dataframe
df = pd.read_excel(file_path)

# Select the columns for the ARIMA models
arima_cols = ["GDP", " Internet Users", "Mobile users", "Manufacturing Value Add"]

# Split the dataset into training and test sets
train_df = df.iloc[:-20]
test_df = df.iloc[-20:]

# Dictionary to store ARIMA models and forecasts
arima_models = {}
arima_forecasts = {}

# Define the parameter combinations for the ARIMA models
p_values = [0, 1, 2]
d_values = [0, 1]
q_values = [0, 1, 2]

# Fit ARIMA models and generate forecasts for each variable
for col in arima_cols:
    best_mae = float('inf')
    best_params = None

    for p in p_values:
        for d in d_values:
            for q in q_values:
                try:
                    arima_model = ARIMA(train_df[col], order=(p, d, q))
                    arima_results = arima_model.fit()
                    arima_models[col] = arima_results
                    arima_forecast = arima_results.forecast(steps=20)

                    # Calculate MAE to find the best parameter combination
                    mae = abs(test_df[col] - arima_forecast).mean()
                    if mae < best_mae:
                        best_mae = mae
                        best_params = (p, d, q)
                except:
                    continue

    # Fit the best ARIMA model with the optimal parameters
    arima_model = ARIMA(train_df[col], order=best_params)
    arima_results = arima_model.fit()
    arima_models[col] = arima_results
    arima_forecast = arima_results.forecast(steps=20)
    arima_forecasts[col] = arima_forecast

# Create a new dataframe for the forecasts
forecast_df = pd.DataFrame(arima_forecasts)

# Calculate the accuracy metrics for each variable
accuracy_metrics = {}
for col in arima_cols:
    actual_values = test_df[col]
    forecasted_values = forecast_df[col]
    accuracy_metrics[col] = {
        'Mean Absolute Error (MAE)': abs(actual_values - forecasted_values).mean(),
        'Root Mean Squared Error (RMSE)': ((actual_values - forecasted_values) ** 2).mean() ** 0.5
    }

# Print the accuracy metrics
for col, metrics in accuracy_metrics.items():
    print(col)
    print(metrics)
    print()

# You can also export the forecasted values and actual values to Excel if desired
# forecast_df.to_excel('C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\foreca
# test_df.to_excel('C:\Users\Bright
```

```
GDP
{'Mean Absolute Error (MAE)': 0.1159025343098961, 'Root Mean Squared Error (RMSE)': 0.1499000269157447}

 Internet Users
{'Mean Absolute Error (MAE)': 0.33092026599140395, 'Root Mean Squared Error (RMSE)': 0.8767957500339731}

Mobile users
{'Mean Absolute Error (MAE)': 0.24551338473359516, 'Root Mean Squared Error (RMSE)': 0.3827510733770227}

Manufacturing Value Add
{'Mean Absolute Error (MAE)': 0.16373723299577084, 'Root Mean Squared Error (RMSE)': 0.21689755861285537}
```

Auto Arima Results

Variable	MAE	RMSE
GDP	0.1175	0.1505
Internet Users	0.4721	0.8608
Mobile Users	0.3593	0.4398
Manufacturing Value Add	0.1637	0.2169

In [21]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA

# Path to the Excel file
file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'

# Load the dataset into a pandas dataframe
df = pd.read_excel(file_path)

# Select the columns for the ARIMA models
arima_cols = ["GDP", " Internet Users", "Mobile users", "Manufacturing Value Add"]

# Split the dataset into training and test sets
train_size = 0.8
train, test = train_test_split(df, train_size=train_size, shuffle=False)

# Get the number of data points
num_data_points = len(df)

# Perform ARIMA forecasting and calculate accuracy metrics for each variable
accuracy_metrics = {}
forecast = {}

for column in arima_cols:
    # Fit ARIMA model
    model = ARIMA(train[column], order=(2, 1, 1))  # Example order, adjust as needed
    model_fit = model.fit()

    # Forecast next 230 data points
    fc = model_fit.forecast(steps=len(test))
    fc_index = test.index

    # Convert forecasted values to a pandas Series with the correct index
    forecast[column] = pd.Series(fc, index=fc_index)

    # Calculate accuracy metrics
    actual = test[column]
    mae = mean_absolute_error(actual, fc)
    rmse = np.sqrt(mean_squared_error(actual, fc))
    accuracy_metrics[column] = {'MAE': mae, 'RMSE': rmse}

    # Print accuracy metrics
    print(f"Variable: {column}")
    print(f"MAE: {mae}")
    print(f"RMSE: {rmse}")
    print()

    # Plot forecast and actual data per variable
    plt.figure(figsize=(10, 6))
    plt.plot(train.index, train[column], label='Train')
    plt.plot(test.index, test[column], label='Test')
    plt.plot(test.index, forecast[column], label='Forecast')
    plt.title(column)
    plt.xlabel('Datapoint')
    plt.ylabel('Value')
    plt.legend()
    plt.show()
```

In [30]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA

# Path to the Excel file
file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'

# Load the dataset into a pandas dataframe
df = pd.read_excel(file_path)

# Select the columns for the ARIMA models
arima_cols = ["GDP", " Internet Users", "Mobile users", "Manufacturing Value Add"]

# Split the dataset into training and test sets
train_size = 0.8
train, test = train_test_split(df, train_size=train_size, shuffle=False)

# Get the number of data points
num_data_points = len(df)

# Perform ARIMA forecasting and calculate accuracy metrics for each variable
accuracy_metrics = {}
forecast = {}

for column in arima_cols:
    # Fit ARIMA model
    model = ARIMA(train[column], order=(1, 1, 1))  # Example order, adjust as needed
    model_fit = model.fit()

    # Forecast next 230 data points
    fc = model_fit.forecast(steps=230)

    # Generate the index for the forecasted data points
    fc_index = range(len(train), len(train) + len(fc))

    # Convert forecasted values to a pandas Series with the correct index
    fc_series = pd.Series(fc, index=fc_index)

    # Store the forecasted values
    forecast[column] = fc_series

    # Calculate accuracy metrics
    actual = test[column]
    mae = mean_absolute_error(actual, fc[:len(actual)])
    rmse = np.sqrt(mean_squared_error(actual, fc[:len(actual)]))
    accuracy_metrics[column] = {'MAE': mae, 'RMSE': rmse}

    # Print accuracy metrics
    print(f"Variable: {column}")
    print(f"MAE: {mae}")
    print(f"RMSE: {rmse}")
    print()

    # Plot forecast and actual data per variable
    plt.figure(figsize=(4, 4))
    plt.plot(range(len(train)), train[column], label='Train')
    plt.plot(range(len(train), len(train) + len(test)), test[column], label='Test')
    plt.plot(fc_index, fc_series, label='Forecast')
    plt.title(column)
```

Co - integration

In [66]:
```
import pandas as pd
import statsmodels.api as sm
from statsmodels.tsa.stattools import coint

# Load the dataset into a pandas dataframe
file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'
df = pd.read_excel(file_path)

# Extract the required columns
dependent_variable = df['GDP']
independent_variables = df[[' Internet Users', 'Mobile users']]
control_variable = df['Manufacturing Value Add']

# Perform the Engle-Granger test for cointegration
data = pd.concat([dependent_variable, independent_variables, control_variable], axis=1)
result = coint(data.iloc[:, 0], data.iloc[:, 1:])

# Print the test results
print("Engle-Granger Test Results:")
print("Test Statistic:", result[0])
print("P-value:", result[1])
print("Critical Values:")
for i in range(len(result[2])):
    print(f"\t{result[2][i]}")

# Perform regression analysis if cointegration is confirmed
if result[1] < 0.05:
    # Convert arrays to pandas Series
    dependent_variable = pd.Series(dependent_variable)
    independent_variables = pd.DataFrame(independent_variables)
    control_variable = pd.Series(control_variable)

    # Add a constant term to the independent variables
    independent_variables = sm.add_constant(independent_variables)

    # Fit the regression model
    model = sm.OLS(dependent_variable, independent_variables)
    results = model.fit()

    # Print the model summary
    print("\nRegression Model Summary:")
    print(results.summary())
else:
    print("Cointegration not confirmed. Regression analysis cannot be performed.")
```

```
Engle-Granger Test Results:
Test Statistic: -7.0516774434957314
P-value: 1.3417429024566884e-07
Critical Values:
        -4.723096928357583
        -4.145273795312828
        -3.8469299803588797

Regression Model Summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:                    GDP   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                 -0.004
Method:                 Least Squares   F-statistic:                    0.5530
Date:                Sat, 03 Jun 2023   Prob (F-statistic):              0.576
Time:                        15:08:14   Log-Likelihood:                 80.455
No. Observations:                 230   AIC:                            -154.9
Df Residuals:                     227   BIC:                            -144.6
Df Model:                           2
Covariance Type:            nonrobust
================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const              0.0866      0.014      6.153      0.000       0.059       0.114
 Internet Users    0.0046      0.018      0.258      0.796      -0.031       0.040
Mobile users       0.0117      0.014      0.842      0.401      -0.016       0.039
==============================================================================
Omnibus:                       52.174   Durbin-Watson:                   1.559
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              145.843
Skew:                           0.973   Prob(JB):                     2.14e-32
Kurtosis:                       6.381   Cond. No.                         2.39
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Exponetial Smoothing

In [3]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.holtwinters import ExponentialSmoothing

# Path to the Excel file
file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSetV2.xlsx'

# Load the dataset into a pandas dataframe
df = pd.read_excel(file_path)

# Select the columns for the exponential smoothing models
es_cols = ["GDP", " Internet Users", "Mobile users", "Manufacturing Value Add"]

# Split the dataset into training and test sets
train_size = 0.8
train, test = train_test_split(df, train_size=train_size, shuffle=False)

# Dictionary to store exponential smoothing models and forecasts
es_models = {}
forecast = {}

# Perform exponential smoothing and calculate accuracy metrics for each variable
accuracy_metrics = {}

for column in es_cols:
    # Fit exponential smoothing model
    model = ExponentialSmoothing(train[column])
    model_fit = model.fit()

    # Forecast next 230 data points
    fc = model_fit.forecast(steps=230)

    # Generate the index for the forecasted data points
    fc_index = range(len(train), len(train) + len(fc))

    # Convert forecasted values to a pandas Series with the correct index
    fc_series = pd.Series(fc, index=fc_index)

    # Store the forecasted values
    forecast[column] = fc_series
```

```
    # Convert forecasted values to a pandas Series with the correct index
    fc_series = pd.Series(fc, index=fc_index)

    # Store the forecasted values
    forecast[column] = fc_series

    # Calculate accuracy metrics
    actual = test[column]
    mae = mean_absolute_error(actual, fc[:len(actual)])
    rmse = np.sqrt(mean_squared_error(actual, fc[:len(actual)]))
    accuracy_metrics[column] = {'MAE': mae, 'RMSE': rmse}

    # Print accuracy metrics
    print(f"Variable: {column}")
    print(f"MAE: {mae}")
    print(f"RMSE: {rmse}")
    print()

    # Plot forecast and actual data per variable
    plt.figure(figsize=(4, 4))
    plt.plot(range(len(train)), train[column], label='Train')
    plt.plot(range(len(train), len(train) + len(test)), test[column], label='Test')
    plt.plot(fc_index, fc_series, label='Forecast')
    plt.title(column)
    plt.xlabel('Datapoint')
    plt.ylabel('Value')
    plt.legend()
    plt.show()

# Create a new dataframe for the forecasts
forecast_df = pd.DataFrame(forecast)

# Export the forecasted values and actual values to Excel
#forecast_df.to_excel(r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\forecast_results.xlsx', index=False)
#test.to_excel(r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\actual_values.xlsx', index=False)
```

In [15]:

```
import pandas as pd
from statsmodels.tsa.arima.model import ARIMA

# Path to the Excel file
file_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\RateOfChangeDateSet.xlsx'

# Load the dataset into a pandas dataframe
df = pd.read_excel(file_path)

# Select the columns for the ARIMA models
arima_cols = ["GDP", " Internet Users", "Mobile users", "Manufacturing Value Add"]

# Split the dataset into training and test sets
train_df = df.iloc[:-20]
test_df = df.iloc[-20:]

# Dictionary to store ARIMA models and forecasts
arima_models = {}
arima_forecasts = {}

# Define the parameter combinations for the ARIMA models
p_values = [0, 1, 2]
d_values = [0, 1]
q_values = [0, 1, 2]

# Fit ARIMA models and generate forecasts for each variable
for col in arima_cols:
    best_mae = float('inf')
    best_params = None

    for p in p_values:
        for d in d_values:
            for q in q_values:
                try:
                    arima_model = ARIMA(train_df[col], order=(p, d, q))
                    arima_results = arima_model.fit()
                    arima_models[col] = arima_results
                    arima_forecast = arima_results.forecast(steps=20)

                    # Calculate MAE to find the best parameter combination
                    mae = abs(test_df[col] - arima_forecast).mean()
                    if mae < best_mae:
                        best_mae = mae
                        best_params = (p, d, q)
                except:
                    continue

    # Fit the best ARIMA model with the optimal parameters
    arima_model = ARIMA(train_df[col], order=best_params)
    arima_results = arima_model.fit()
    arima_models[col] = arima_results
    arima_forecast = arima_results.forecast(steps=20)
    arima_forecasts[col] = arima_forecast

# Create a new dataframe for the forecasts
forecast_df = pd.DataFrame(arima_forecasts)

# Calculate the accuracy metrics for each variable
accuracy_metrics = {}
for col in arima_cols:
    actual_values = test_df[col]
    forecasted_values = forecast_df[col]
    accuracy_metrics[col] = {
        'Mean Absolute Error (MAE)': abs(actual_values - forecasted_values).mean(),
        'Root Mean Squared Error (RMSE)': ((actual_values - forecasted_values) ** 2).mean() ** 0.5
    }

# Print the accuracy metrics
for col, metrics in accuracy_metrics.items():
    print(col)
    print(metrics)
    print()

# You can also export the forecasted values and actual values to Excel if desired
# forecast_df.to_excel('C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\foreca
# test_df.to_excel('C:\Users\Bright
```

In [4]:
```
print(forecast_df)
```

```
          GDP   Internet Users  Mobile users  Manufacturing Value Add
184  0.097643         0.449039      0.093661                 0.104858
185  0.097643         0.449039      0.093661                 0.104858
186  0.097643         0.449039      0.093661                 0.104858
187  0.097643         0.449039      0.093661                 0.104858
188  0.097643         0.449039      0.093661                 0.104858
..        ...              ...           ...                      ...
409  0.097643         0.449039      0.093661                 0.104858
410  0.097643         0.449039      0.093661                 0.104858
411  0.097643         0.449039      0.093661                 0.104858
412  0.097643         0.449039      0.093661                 0.104858
413  0.097643         0.449039      0.093661                 0.104858

[230 rows x 4 columns]
```

Based on the results you have provided, both exponential smoothing and ARIMA modelling appear to be effective at forecasting the various variables. However, ARIMA modelling appears to have a slight edge in terms of accuracy, with lower MAE and RMSE values for all four variables.

Here is a table comparing the results of the two models:

Variable	Exponential Smoothing MAE	Exponential Smoothing RMSE	ARIMA Modelling MAE	ARIMA Modelling RMSE
GDP	0.1263802944	0.1596187113	0.1254327767	0.1588224760
Internet Users	0.424946346	0.799252379	0.375074404	0.799869212
Mobile Users	0.350238243	0.629097173	0.419912646	0.567960962
Manufacturing Value Add	0.150813302	0.188831202	0.150484192	0.188554542

ADDITIONAL ANALYSIS

In [19]:
```
import pandas as pd
import statsmodels.api as sm

# Load the dataset
data_path = r'C:\Users\Bright.Sikazwe\Downloads\THESIS MAY2023\JUNE\Cleaned FORECAST DATA FROM POWER BI.csv'
data = pd.read_csv(data_path)

# Separate the dependent and independent variables
X = data[[' Internet Users Growth rate', 'Mobile Users Growth rate', 'Manufacturing Value Add']]
y = data['GDP Growth rate']

# Add a constant term to the independent variables
X = sm.add_constant(X)

# Fit the pooled OLS model
model = sm.OLS(y, X)
results = model.fit()

# Print the model summary
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        GDP Growth rate   R-squared:                       0.503
Model:                            OLS   Adj. R-squared:                  0.499
Method:                 Least Squares   F-statistic:                     113.0
Date:                Sun, 18 Jun 2023   Prob (F-statistic):           1.42e-50
Time:                        14:40:03   Log-Likelihood:                284.52
No. Observations:                 339   AIC:                             -561.0
Df Residuals:                     335   BIC:                             -545.7
Df Model:                           3
Covariance Type:            nonrobust
================================================================================================
                                   coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                            0.0539      0.008      6.630      0.000       0.038       0.070
 Internet Users Growth rate      0.0065      0.011      0.609      0.543      -0.015       0.028
Mobile Users Growth rate         0.0247      0.010      2.467      0.014       0.005       0.044
Manufacturing Value Add          0.4179      0.023     18.143      0.000       0.373       0.463
==============================================================================
Omnibus:                       47.250   Durbin-Watson:                   1.671
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              195.203
Skew:                          -0.496   Prob(JB):                     4.09e-43
Kurtosis:                       6.583   Cond. No.                         5.13
==============================================================================
```