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Leveraging Smart Technologies for Sustainable Economic Development: Evidence from Urban and Rural Communities in Bulawayo Province, Zimbabwe

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Abstract

The global shift towards digitalization has significantly transformed economic structures, with smart technologies playing a crucial role in reshaping both urban and rural economies. In developing economies, digitalization is increasingly recognized as a key driver of economic growth and competitiveness. This study explores the role of digital innovations, the Internet of Things (IoT), artificial intelligence (AI), and data-driven solutions in enhancing economic resilience and environmental sustainability. In urban areas, smart infrastructure, digital governance, and green energy solutions optimize resource utilization and improve service delivery. Meanwhile, in rural economies, precision agriculture, digital financial services, and mobile connectivity bridge the digital divide, improve productivity, and expand market access for small-scale enterprises. The objective of this paper is to analyse how smart technologies can be leveraged to promote inclusive and equitable economic development in Bulawayo. It seeks to identify innovative solutions, share best practices, and provide policy recommendations that facilitate digital transformation across urban and rural areas. The study adopts a mixed-methods approach, combining qualitative and quantitative research techniques. Primary data is collected through surveys and interviews with policymakers, technology experts, small and medium enterprise (SME) owners, and local community representatives in Bulawayo. The target population comprises approximately 5,000 stakeholders, including digital service providers, urban planners, and rural development officers. A stratified random sampling technique is employed to ensure diverse representation, with a sample size of 350 respondents selected from different sectors, including ICT, agriculture, manufacturing, and commerce. Secondary data is sourced from academic literature, government reports, and industry case studies. To empirically assess the impact of smart technologies on economic sustainability, the study employs an Autoregressive Distributed Lag (ARDL) model to examine short- and long-run relationships between smart technology adoption and key economic indicators, including GDP growth, employment rates, and environmental sustainability indices. Additionally, a Difference-in-Differences (Did) approach is used to evaluate the causal impact of digital infrastructure investments on rural and urban economic outcomes. The findings reveal that while smart technologies drive efficiency, reduce carbon footprints, and enhance productivity, challenges such as digital exclusion, infrastructure deficits, and policy gaps hinder widespread adoption while employment variable was significant suggesting that employment gains may enhance output after a time lag once productivity and skills catch up. In the rural economy there remains significant barriers to digital integration while inclusion strategies, such as affordable device programs, internet subsidies, and community-based digital training can be persuade. In conclusion, the study underscores the need for strategic investments in digital ecosystems, public-private partnerships, and inclusive policy frameworks to ensure that technological advancements benefit all sectors of society. By leveraging smart technologies, urban and rural economies can achieve sustainable economic growth while addressing social and environmental challenges.

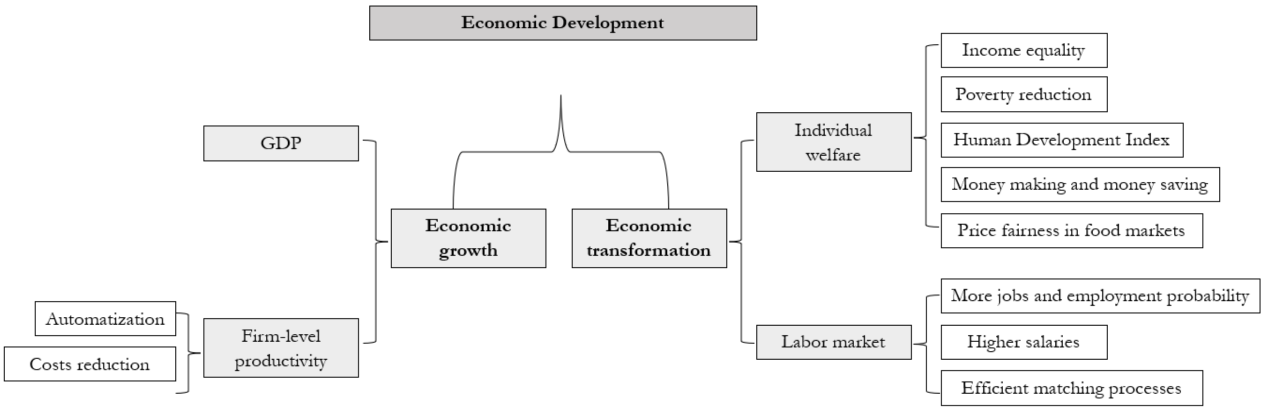
Keywords: Smart technologies, sustainable development, urban economies, rural economies, digital transformation, economic resilience, ARDL model, Difference-in-Differences (DiD), Bulawayo, inclusive economic development

1. Introduction

The global shift towards digitalization has significantly transformed economic structures, with smart technologies playing a crucial role in reshaping both urban and rural economies (Schwab, 2016). The advent of digital innovations such as artificial intelligence

(AI), blockchain, big data analytics, and the Internet of Things (IoT) has enhanced efficiency, economic productivity, and service delivery (Brynjolfsson & McAfee, 2017). Kabongo and Okpara (2014; 315) define digitalisation as "any communication device or application, including radio, television, mobiles phones, computers, network hardware and software and satellite systems…and any associated applications." Solomon (2020) also points out that digital technology has transformed how firms operate globally. This transformation has been particularly notable in developed economies including Africa, where the integration of digital solutions has improved governance, business operations, education, healthcare, and environmental sustainability (World Economic Forum, 2020). Digital technologies have also facilitated "datafication" and "virtualisation" (Bukht & Heeks, 2017). De' et al., 2020 posits that the significance of digital technology has rarely been greater understood than during the 2020 global economic shutdown as a result of the COVID-19 pandemic. Cobos & Malásquez (2023) in their study found out that digitization brings economic transformation and economic growth together as shown in figure 1 below.

Figure 1: Effects of ICT towards Economic Growth.



Adapted from: Cobos & Malásquez, 2023

In developing economies, digitalization is increasingly recognized as a key driver of economic growth and competitiveness (Ndulu & O'Connell, 2020). However, the rate of digital adoption varies significantly between urban and rural communities, often exacerbating existing socio-economic inequalities. Zimbabwe economy has been on the doldrums for the past two decades and the country has generally lagged behind in digital integration. The inception of the US dollar since government of national unity has somehow enhanced adoption of digital technology despite that the economy continues to navigate through oscillating macroeconomic instability. In Bulawayo, Zimbabwe's second-largest city, digitalization is a strategic approach to addressing pressing challenges related to economic development, service delivery, and environmental management (Mugari & Chirisa, 2021). The city has witnessed gradual advancements in digital infrastructure, particularly in sectors such as banking, education, and public administration. Nevertheless, disparities in access to and utilization of digital technologies persist, limiting the full potential of these innovations (Chigunwe, 2022). Several factors contribute to the digital divide in Bulawayo. These include inadequate infrastructure, high costs of digital devices and internet services, limited digital literacy, and resistance to technological change among certain demographic groups (Mlambo & Moyo, 2023). The gap is more pronounced between urban and rural communities, with rural areas experiencing lower levels of connectivity and fewer opportunities for technological integration (Zhou et al., 2021). This digital disparity hinders inclusive growth and restricts access to essential services such as online education, e-health, and digital financial services (UNCTAD, 2022).

Consequently, addressing these challenges requires a multi-faceted approach involving public-private partnerships, investment in digital infrastructure, capacity-building initiatives, and policy reforms (World Bank, 2021). Encouragingly, the government of Zimbabwe has recognized the importance of digital transformation and has introduced policies aimed at promoting digital inclusion and smart city initiatives (Government of Zimbabwe, 2023). However, effective implementation remains a critical challenge due to financial constraints, bureaucratic inefficiencies, and resistance to change (Nyoni, 2024). Given the crucial role of digitalization in fostering economic resilience, it is imperative to explore sustainable strategies for enhancing digital adoption across different socio-economic segments. Therefore, this study aims to examine the determinants of digital technology adoption in Bulawayo, focusing on the impact of socio-economic factors, policy frameworks, and technological infrastructure on digital transformation efforts. While smart technologies have the potential to drive economic development, their impact in Bulawayo remains underexplored. There is a need to investigate how digital tools can enhance productivity, reduce economic inequality, and promote sustainable development in both urban and rural settings (Mhlanga, 2022).

1.2 Research Objective

This paper aims to:

i. Evaluate the impact of smart technologies on economic development in Bulawayo.
ii. Identify the key barriers to digital adoption in urban and rural economies.
iii. Provide evidence-based policy recommendations to enhance digital transformation for sustainable economic growth.

2. Review of Literature

2.1 Digitalisation Theories

Diffusion of Innovation Theory

The theory was propounded by Rogers (1950) who postulated that new ideas, practices or objects are adopted by individuals and organisations. The theory alludes that there are three sets of variables that influence the acceptance of innovations. Prior conditions provide a context for the consideration of changes by adopters. Examples include previous practices, felt needs or problems, innovativeness as a characteristic of the individual or organization, and norms (expectations) of the social system in which the adoption occurs. Adoption of technologies is influenced by characteristics that include socioeconomic factors (age, education, status, financial well-being, etc.), personality variables (curiosity, open-mindedness, etc.), and communication behaviours. Moreso, characteristics of the innovation itself influence acceptance. The theory further emphasizes that innovations are more likely to gain acceptance if they provide a relative advantage compared to the ideas they replace or to alternative solutions. Acceptance is also more likely when innovations offer compatibility with existing processes or ideas, simplicity (versus complexity), trialability (the ability to experiment on a limited and risk-free basis), and observability (being tangible and readily inspected). Rogers posited that the adoption rate for innovations follows an S-shaped curve in which adoption begins slowly but rapidly escalates once a critical mass is achieved. Rates of adoption will then taper off after reaching a peak. The relative steepness or shape of the S-curve explains how some innovations are quickly adopted (sharp, steep rise) or require longer times for acceptance (a wider, flatter curve). The theory has been found to be applicable in Africa including Zimbabwe. Zimbabwean economy adoption rate of technology is influenced socioeconomic factors. In a well performing economy with an educated workforce and stable incomes Bulawayo citizens and enterprises are likely to adopt new technologies for economic and social growth.

Resource based View Theory

Initially put out by Barney (1991), the Resource-Based View (RBV) holds that a company acquires a durable competitive advantage by means of development and use of special resources and skills. It involves using big data analytics, blockchain technology, sophisticated cybersecurity infrastructure, and artificial intelligence financial services in the banking industry (Barney & Hesterly, 2019). Mango et al (2025) found out that banks use blockchain technology, big data analytics and cloud-based infrastructure. Nyathi and Chikwala (2024) reveal that industries in Bulawayo including SMEs are adopting robotics technology to remain competitive in the manufacturing sector. This is consistent with the RBV paradigm, which underlines the need of valuable, rare, inimitable, and non-substitutable (VRIN) resources in reaching market distinction (Moloiswa, 2025).

The Dynamic Capability Theory

The theory emphasises the requirement of ongoing adaptability and creativity. The capability approach to digital transformation focuses on developing and leveraging an organization's specific digital capabilities its ability to integrate IT and organizational resources to adapt to market demands. It is especially important in smart technology adoption were government departments and the private sector are adopting to smart technology to improve efficiency, reduce costs, enhance customer service delivery and improve production output. Dynamic capabilities imply that government departments, banks and private sector have to not only acquire technology resources but also constantly reorganise their digital strategy to be relevant in the face of changing markets (Ishak et al., 2023).

2.2 Comparative Analysis of Digitalization Adoption in Africa: Lessons for Zimbabwe

The digital economy in the Global South is a paradox. On the one hand, it holds the promise of addressing socioeconomic inequalities by allowing citizens to engage in innovative economic activities and join the global digitalised economy. On the other hand, it has the potential to widen socioeconomic gaps by relegating Global South citizens to passive consumers who do not reap the economic benefits of the Internet, widening the gap between haves and have-nots (Wyk-Khosa, 2025). Since the 1990s, the rapid expansion of the Internet has been closely linked to economic growth in many countries around the world, paving the way for digital economies (Ndoya & Asonga, 2024). In developing countries, the digital economy is experiencing faster growth than the rest of the economy and thus plays a significant role in creating employment opportunities (Bukht & Heeks, 2018; OECD, 2024). South Africa and Mauritius on the African continent are the digital economy leaders, the information and communication technologies (ICT) sector contributes to a sizeable portion of the countries' gross domestic products (GSMA, 2024; Mubika, 2025).Despite the digital economy offering higher-than-average wages and new markets for start-ups, it also comes with an important downside: Those who are on the wrong side of the digital divide often do not have the necessary devices, reliable access to electricity and the Internet, or the skills necessary to use the Internet advantageously in the digital labour market (Ndoya & Asonga, 2024; Ragnedda & Gladkova, 2020). Sub-Saharan Africa (SSA) faces critical challenges for digital development, including underdeveloped digital infrastructure, lack of accessible and affordable connectivity, a stubborn digital gender gap, limited skills for digitally enabled industries, and inadequate regulatory and policy environments. However, in the last decade, the region has made substantial strides toward digital transformation, with hundreds of millions of people gaining access to the internet and productively utilizing a wide variety of digital services, such as mobile payments and online learning platforms. According to World Bank over 160 million Africans gained broadband internet access between 2019 and 2022. There has been an increase of 115 percent increase in internet users between 2016 and 2021, 191 million additional individuals made or received a digital payment between 2014 and 2021 in Sub-Saharan Africa (World Bank, 2025).

Zimbabwe, once known as "the jewel of Africa" for its great prosperity, has been experiencing prolonged economic distress over the past two decades due to external shocks and internal instability. The COVID-19 pandemic has exacerbated the already difficult macroeconomic situation in the country, further worsening economic and social conditions. The Government of Zimbabwe recognizes that sound macroeconomic management and improved governance are key for setting the country back on the path to prosperity. The information and communication technology (ICT) sector, lying at the core of the digital economy, is recognized as central to turning around the Zimbabwean economy. It has a bearing on most business activities in the private and public sector and in the daily lives of the citizens. In 2019, it was the fastest growing sector in the economy in Zimbabwe. The ongoing macroeconomic woes have provided both a challenge for the further development of ICT, but also an opportunity for innovation and urgent reform (World Bank, 2021).

2.3 Urban vs. Rural Technological Adoption

Studies indicate that urban areas tend to adopt smart technologies faster due to better infrastructure, higher internet penetration, and greater availability of digital resources, whereas rural communities often lag due to inadequate connectivity, low digital literacy, and financial constraints (World Bank, 2021). This urban-rural divide is particularly evident in sub-Saharan Africa, where digital disparities persist despite efforts to promote inclusivity (ITU, 2022).
Further, urban areas typically benefit from advanced telecommunication networks, greater investment in digital services, and stronger institutional support, which enable faster adoption of AI, IoT, and mobile banking services (Gillwald et al., 2019). While on the same note, Mugari & Chirisa (2021) reveal that cities like Bulawayo have seen rapid growth in fintech solutions, smart public transport systems, and e-government services, fostering economic efficiency and improving quality of life.

Conversely, rural communities face several barriers to digital adoption. Limited access to affordable internet, inadequate power supply, and a lack of technical skills hinder the integration of smart technologies (Zhou et al., 2021). In addition, digital illiteracy among rural populations further limits engagement with digital platforms, restricting access to essential services such as online banking, telemedicine, and digital education (Chigunwe, 2022).
Policymakers have recognized the urgency of addressing these disparities, leading to various initiatives such as rural connectivity projects, mobile network expansion, and digital literacy programs (Government of Zimbabwe, 2023). However, challenges such as high costs of deployment, resistance to change, and limited funding continue to slow progress (Nyoni, 2024). Bridging this gap requires a multi-stakeholder approach, involving government agencies, private sector investments, and community-driven initiatives to ensure sustainable and inclusive digital transformation (UNCTAD, 2022).

3. Methodology

3.1 Research Design

A mixed-methods approach is employed, integrating both qualitative and quantitative data to ensure a comprehensive analysis of smart technology adoption in Bulawayo. This approach allows for an in-depth understanding of economic, social, and policy-related factors influencing digital transformation (Creswell & Clark, 2018).

3.2 Data Collection

- Primary Data: Surveys and semi-structured interviews with 350 respondents drawn from a target population of 5,000 stakeholders, including policymakers, business owners, digital service providers, and end-users. The surveys capture data on digital access, adoption patterns, and perceived benefits or challenges, while interviews provide deeper insights into stakeholder perspectives (Kothari, 2004).
- Secondary Data: Analysis of government reports, academic research, industry case studies, and international digital economy reports to provide contextual and comparative insights (World Bank, 2021).

3.3 Econometric Modelling

Autoregressive Distributed Lag (ARDL) Model – This model assesses the short- and long-run relationships between smart technology adoption and economic indicators such as GDP growth, employment rates, and smart technology adoption indices (Pesaran et al., 2001). The ARDL approach is well-suited for analysing time-series data and capturing dynamic relationships among variables. The model specification is:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=0}^{q} \gamma_j X_{t-j} + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 1$$

Where:

Y_t represents the dependent variable (economic indicator),
X_t represents independent variables (smart technology adoption, digital investment, etc.),
α is the intercept, and ε_t is the error term.

If we specify an ARDL model with GDP Growth Rate (GDP_G) as the dependent variable, the model takes the form:

$$GDP_{Gt} = \alpha + \sum_{i=1}^{p} \beta_i GDP_{Gt-i} + \sum_{j=0}^{q1} \gamma_j STA_{t-j} + \sum_{k=0}^{q2} \delta_k EMP_{t-k} + \lambda\, Time + \varepsilon_t \dots\dots\dots\dots\dots 2$$

Where:

GDP_{Gt} (Dependent Variable): Economic growth measured by GDP Growth Rate, in percentage terms.
Lagged values of GDP Growth Rate (GDP_{Gt-i}): Capture the autoregressive component.
STA_{t-j} (Smart Technology Adoption Index, 0-100 scale, Independent Variable): Measures the extent of technological adoption.
EMP_{t-k} (Employment Rate, in percentage terms, Independent Variable): Reflects labor market conditions.
Time (Years from 2000 to 2024) controls for potential time trends

Difference-in-Differences (DiD) Approach

The study also makes use of the differences in differences method which aims to cancel out the bias caused by unobservable confounders (Li, Anon). Card & Krueger, (1994) weighs in and mention that the approach is used to evaluate the impact of digital infrastructure investments on economic outcomes before and after implementation in different communities. Fougere & Jacquemet (2023) argue that the difference-in-differences method is a quantitative, quasi-experimental method to assess the impact of an intervention by setting up comparison groups and measuring the change in an outcome between a pre- and a post-intervention period when only one of the two groups has access to the intervention. This method is very useful for ex-post impact evaluation. Baker et al (2025) postulate that the difference-in-differences (DiD) is now the most common research design for estimating causal effects between two time periods, one before and one after some treatment begins, and two groups, one that receives a treatment and one that does not.
The DiD model specification is:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treat_i + \beta_3 (Post_t \times Treat_i) + \varepsilon_{it}$$

Where:
Y_{it} is the outcome variable,
$Post_t$ is a dummy variable for the post-intervention period,
$Treat_i$ is a dummy for treatment group,
$Post_t \times Treat_i$ captures the treatment effect.

$$GDP_{Git} = \beta_0 + \beta_1 Post_t + \beta_2 Treat_i + \beta_3 (Post_t \times Treat_i) + \varepsilon_{it}$$

GDP_{Git} (Dependent Variable):

The economic outcome being analysed (GDP Growth Rate, in percentage terms).
$Post_t$ (Post-Intervention Dummy):
1 if the observation is from the post-digital infrastructure investment period.
0 if from the pre-investment period.
$Treat_i$ (Treatment Dummy):
1 if the observation is from a community that received digital infrastructure investment.
0 if from a control community that did not receive investment.
$Post_t \times Treat_i$ (Interaction Term):
Captures the treatment effect (i.e., the difference in GDP growth rate changes between treated and control groups before and after the investment).
β_0: Intercept (baseline GDP growth rate before investment).
β_1: Captures changes in GDP growth over time, affecting both treatment and control groups.
β_2: Captures baseline differences between treatment and control groups.
β_3: The DiD estimator, measuring the causal effect of digital infrastructure investments on GDP growth.

4 Results and Discussion

4.1 Descriptive Statistics

Table 1: Descriptive Statistics

	GDP_G	STA	EMP
Mean	0.223782	40.27076	54.32287
Median	0.760000	40.30115	54.17306
Maximum	19.68000	72.93429	64.58396
Minimum	-17.67000	2.923146	46.44348
Std. Dev.	9.027826	20.02787	4.698040
Skewness	0.216109	-0.109608	0.157950
Kurtosis	3.127647	1.966392	2.304014
Jarque-Bera	0.211569	1.162918	0.608531
Probability	0.899618	0.559082	0.737665
Sum	5.594557	1006.769	1358.072
Sum Sq. Dev.	1956.039	9626.769	529.7179
Observations	25	25	25

Source: E-views 10, 2025

The descriptive statistics for the period 2000 to 2024 reveal important insights into Zimbabwe's economic dynamics, particularly in relation to GDP growth (GDP_G), Smart Technology Adoption (STA), and Employment (EMP). The average GDP growth rate over the 25-year period is low, at 0.22%, with a standard deviation of 9.03%, indicating significant volatility and periods of economic instability. The presence of extreme values such as a maximum growth of 19.68% and a minimum of -17.67% suggests that the economy experienced both sharp expansions and contractions, possibly due to external shocks, political uncertainty, or policy shifts. Despite this, the GDP growth data appears approximately normally distributed, as confirmed by a Jarque-Bera p-value of 0.899.

In contrast, smart technology adoption (STA) shows considerable improvement over the period, with a mean of 40.27 and a high standard deviation of 20.03, reflecting significant disparities in adoption levels, particularly between rural and urban settings or public and private sectors. The minimum value of 2.92 likely reflects initial low levels of technological infrastructure, while the maximum of 72.93 points to recent progress. The distribution of STA is nearly symmetric and statistically normal (p = 0.559), which suggests a gradual but uneven diffusion of technology.
Employment (EMP), on the other hand, remains relatively stable over time, with a mean of 54.32 and a narrow standard deviation of 4.70. The range between the maximum (64.58) and minimum (46.44) suggests moderate variation in employment outcomes, likely influenced by broader economic and technological changes. Like GDP_G and STA, EMP is also approximately normally distributed (p = 0.738), with little evidence of extreme skewness or kurtosis. Taken together, these findings underscore a context of economic volatility, advancing digitalisation, and relatively stable labor market conditions, which provide a foundation for evaluating the socio-economic impacts of smart technologies and inclusive growth policies.

4.2 Unit Root Test

Table 2: Unit Root Test

Variable	ADF Test Statistic	1% Critical Value	p-value	Stationary?	Order of Integration
D(LOGSTA)	-7.8313	-3.7529	0.0000	Yes	I(1)
D(EMP)	-4.8332	-3.7245	0.0011	Yes	I(1)
D(GDP_G)	-5.5404	-3.7245	0.0002	Yes	I(1)

Source; Eviews 10, 2025

The Augmented Dickey-Fuller (ADF) test results strongly reject the null hypothesis that the variables D(LOGSTA), D(EMP), and D(GDP_G) each have a unit root, indicating that all three series are stationary at first difference. For D(LOGSTA), the test statistic of -7.8313 is well below the 1% critical value (-3.7529) with a p-value of 0.0000, confirming significance. Similarly, D(EMP) has an ADF statistic of -4.8332 (p = 0.0011), also significant at the 1% level, while

D(GDP_G) shows an ADF statistic of -5.5404 (p = 0.0002), again confirming stationarity.

The high R-squared values and significant F-statistics across the models further reinforce the reliability of these findings. Overall, the results suggest that the first-differenced forms of sectoral employment (EMP), financial development (LOGSTA), and GDP growth (GDP_G) are integrated of order one, I(1), and suitable for further time series analysis, such as cointegration or vector error correction modelling.

4.3 Normality Test

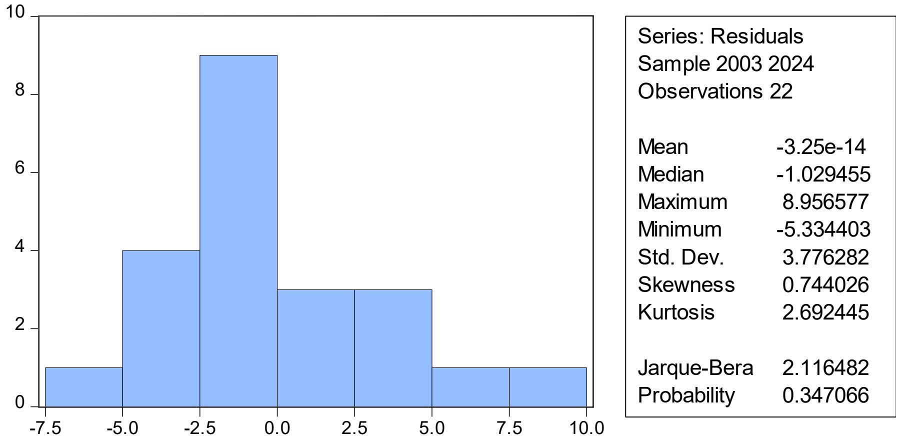


Figure 2: Normality Test

The residual diagnostic results for the regression model covering the period 2003 to 2024 indicate that the model is statistically sound and well specified. The mean of the residuals is approximately zero (−3.25e−14), suggesting no systematic bias in the model's predictions. The standard deviation of 3.78 reflects moderate variability in the prediction errors. The distribution of residuals exhibits slight positive skewness (0.744), indicating a mild tendency for positive errors, while the kurtosis value of 2.69 suggests a distribution with slightly lighter tails than a normal distribution. Importantly, the Jarque-Bera statistic of 2.12 and the corresponding p-value of 0.347 imply that the residuals do not significantly deviate from normality. This is further supported by the histogram, which shows a reasonably symmetric and bell-shaped distribution centered around zero. Overall, the residual analysis confirms that the regression model satisfies the normality assumption, enhancing the reliability of the estimated coefficients and inferential statistics.

4.4 Diagnostic Tests

Table 3: Diagnostic Tests

Test	Statistic	Value	Degrees of Freedom (df)	p-Value	Decision
Breusch-Godfrey LM Test	F-statistic	2.467973	(2, 9)	0.1345	Fail to reject H_0 (no serial correlation)
Heteroskedasticity (BPG Test)	F-statistic	0.595205	(11, 13)	0.7793	Fail to reject H_0 (homoskedasticity)
	Obs*R-squared	6.785267	11	0.6595	Fail to reject H_0
Ramsey RESET Test	t-statistic	0.614334	11	0.5515	Fail to reject H_0 (no misspecification)
	F-statistic	0.377406	(1, 11)	0.5515	Fail to reject H_0

Source: E-views 10, 2025

The Breusch-Godfrey Serial Correlation LM Test was used to detect autocorrelation in the residuals of the model. The F-statistic value of 2.468 (p = 0.1345) suggests that the null hypothesis of no serial correlation cannot be rejected at the 5% level. Meanwhile, the Breusch-Pagan-Godfrey Heteroskedasticity Test indicates no evidence of heteroskedasticity in the residuals. The F-statistic of 0.595 (p = 0.7793) and the Obs*R-squared statistic of 6.785 (p = 0.6595) are both insignificant, leading to the conclusion that the error terms have constant variance (i.e., homoscedasticity), thus satisfying one of the key OLS assumptions.

While on the same note, the Ramsey RESET Test was conducted to assess the model's functional form. The t-statistic (0.6143) and F-statistic (0.3774) both have p-values of 0.5515, indicating that the null hypothesis of correct model specification cannot be rejected. This means there is no strong evidence of omitted variable bias or misspecification, and the linear functional form appears appropriate for the data.

4.5 Model Specification

Table 4: Model Specification

Ramsey RESET Test			
	Value	df	Probability
t-statistic	0.614334	11	0.5515
F-statistic	0.377406	(1, 11)	0.5515

Source: E-views, 2025

The above table indicate the results of the Ramsey RESET test in the regression model is correctly specified. The test yielded a t-statistic of 0.6143 and an F-statistic of 0.3774, with a corresponding p-value of 0.5515. Since the p-value is greater than the conventional 5% significance level, we fail to reject the null hypothesis that the model is correctly specified. This suggests that there is no significant evidence of omitted nonlinear relationships or functional form misspecification. Therefore, the model does not suffer from major specification errors, and its structure can be considered appropriate for explaining the variation in GDP growth based on the selected explanatory variables and their lags.

4.6 Economic Impact of Smart Technologies

Table 5: Economic Impact of Smart Technologies

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
GDP_G(-1)	0.639062	0.136104	4.695398	0.0005
LOGSTA	-8.617517	7.637234	-1.128356	0.2812
LOGSTA(-1)	-7.563272	7.574129	-0.998567	0.3377
LOGSTA(-2)	-8.731845	7.086612	-1.232161	0.2415
LOGSTA(-3)	17.98873	4.214557	4.268236	0.0011
EMP	0.428259	0.257667	1.662060	0.1224
EMP(-1)	-0.232167	0.264070	-0.879189	0.3966
EMP(-2)	-0.649510	0.260072	-2.497426	0.0280
EMP (-3)	0.549695	0.279452	1.967048	0.0727
C	24.43217	26.00035	0.939686	0.3659
R-squared	0.838567	Mean dependent var		0.732480
Adjusted R-squared	0.717492	S.D. dependent var		9.398701
S.E. of regression	4.995552	Akaike info criterion		6.357928
Sum squared resid	299.4664	Schwarz criterion		6.853856
Log likelihood	-59.93721	Hannan-Quinn criter.		6.474754
F-statistic	6.926010	Durbin-Watson stat		2.025408
Prob(F-statistic)	0.001426			

Source: E-views 10, 2025.

The ARDL (1, 3, 3) model examining the impact of smart technology adoption (LOGSTA) and employment (EMP) on GDP growth (GDP_G) over the period 2003–2024 demonstrates a strong overall fit, with an R-squared value of 0.839 and an adjusted R-squared of 0.717. The model is statistically significant at the 1% level (F-statistic = 6.93, p = 0.0014), and the Durbin-Watson statistic of 2.03 suggests no autocorrelation in the residuals. The lagged dependent variable GDP_G (-1) is highly significant (p = 0.0005), indicating strong persistence in economic growth over time.

Smart technology adoption exerts a positive and statistically significant influence on GDP growth with a lag of three years. Specifically, the coefficient of LOGSTA (-3) is 17.99 (p = 0.0011), suggesting that investments in smart technologies require a gestation period before yielding measurable economic benefits. The significance of smart technology adoption (STA) is similar to results of Bukht & Heeks (2017) who found out that digitalisation creates economic growth. Further, Cobos & Malasquez (2023) reveal that there is a positive relationship between the adoption of information and communications technology and country economic growth. Meanwhile, Alawneh & Alosheibat (2023) results also confirm that economic growth is greatly affected by technology. Earlier lags of LOGSTA and its current value are statistically insignificant, indicating that short-term effects are either minimal or obscured by initial adoption challenges. This is consistent with studies of Lenchman & Ewa (2013) who studies 20 Latin American countries who saw significant impact of ICT adoption towards economic growth though adoption rates differed due to size of economy and performance.

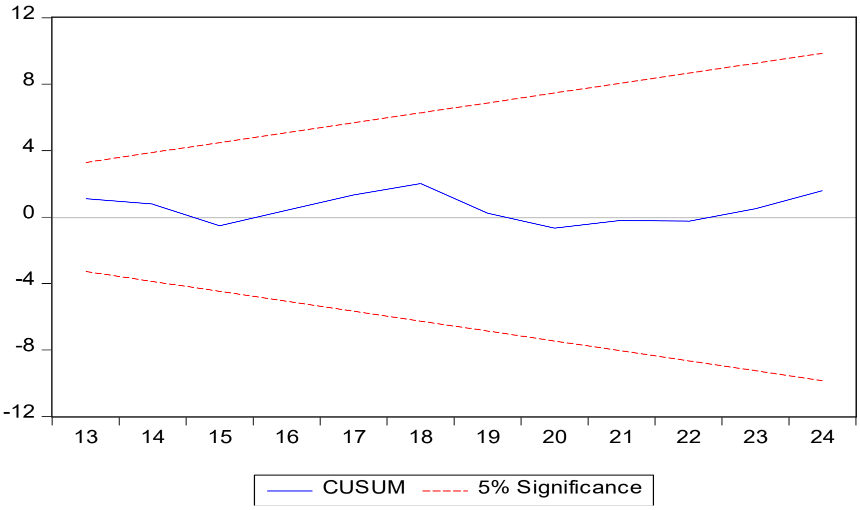
While on the same note, the employment variable posted mixed results. While current and first-lagged employment levels are not significant predictors of GDP growth, the second lag (EMP(-2)) has a negative and statistically significant coefficient (-0.649, $p = 0.028$), implying that employment growth two years prior may have been driven by less productive or informal job creation. However, the third lag of employment (EMP (-3)) is positively associated with GDP growth and marginally significant ($p = 0.073$), suggesting that employment gains may enhance output after a time lag once productivity and skills catch up. The quality of human capital has been emphasised in the literature as a complementary factor in the ICT-growth relationship. Therefore, investment in human capital is an important policy consideration to improve the growth effects of ICT. Ngundu et al (2018) alludes that a long-run equilibrium relationship between manufacturing GDP and formal employment, which implies that increasing manufacturing activities through value addition and beneficiation may provide a long-lasting solution to creating formal jobs in the country.

Overally, the results indicate that smart technology adoption is a key driver of long-run economic growth in Bulawayo, albeit with a delayed effect, while employment dynamics require deeper structural analysis to distinguish between productive and unproductive labor market trends. Bulawayo as the second largest city in Zimbabwe and a former industrial hub, has gone through significant changes in the employment dynamics due to fluctuations, deindustrialisation and economic policies over the years. The findings highlight the importance of sustained investment in digital infrastructure and the need for complementary policies that improve the quality and productivity of employment over time.
The integration of smart technologies across Bulawayo's urban and rural sectors has shown considerable potential to drive inclusive and sustainable economic growth. Quantitative analysis using the Autoregressive Distributed Lag (ARDL) model reveals a statistically significant long-run relationship between smart technology adoption and economic indicators such as GDP growth and employment rates. In the short run, the effects were positive though less pronounced, suggesting a lag in the diffusion of technological benefits.

Urban economies experienced notable improvements in service delivery and resource optimization through the deployment of smart infrastructure, digital governance platforms, and green energy systems. Respondents from the ICT and municipal sectors indicated that smart traffic systems, solar-powered street lighting, and e-governance platforms led to operational efficiencies and enhanced urban mobility. The findings are in tandem with Lenchman& Ewa (2013)'s findings who claim that extraordinary spread of new information and communication (ICTs) technologies is broadly perceived as tools facilitating economic growth and development, especially in economically backward countries. They are relatively easy and cheap to adopt, require minimum skills for effective usage, bringing opportunities for disadvantaged societies. They enable education, knowledge dissemination and sharing, processing and storing all kinds of information. At a time, existence of extend causal relationships between technology diffusion and general economy performance is highly probable.

In rural settings, smart technologies contributed to improved productivity and market access. The use of precision agriculture tools, mobile-based extension services, and digital financial platforms empowered small-scale farmers and entrepreneurs. The study observed that mobile connectivity significantly enhanced access to pricing information, agricultural inputs, and digital payments, thereby reducing transaction costs and increasing market participation. The findings are consistent with the research of Tengeh et al (2023) were in their study they found out that rural entrepreneurs of Gokwe district appreciated the role of digital technology in facilitating networking activities, connecting users, and interacting with suppliers, distributors, customers, and markets to foster their performance and profitability.

4.7 Model Stability Chart



4.7 Figure 3: Model Stability Chart

The CUSUM (Cumulative Sum) stability test graph presented evaluates the stability of the estimated coefficients in the regression model over the sample period. The blue line represents the cumulative sum of recursive residuals, while the red dashed lines denote the 5% significance boundaries.

From the graph, it is clear that the CUSUM line remains within the 5% critical bounds throughout the sample period (2013–2024). This indicates that there is no structural break or instability in the model parameters during this period. In other words, the regression coefficients are stable over time, reinforcing the robustness of the model. The model's predictive power and reliability are thus preserved throughout the entire sample period. This result supports the validity of long-run inferences and confirms that the model does not suffer from misspecification due to parameter instability.

4.8 Difference-in-Differences (DiD) analysis

Difference-in-Differences (DiD) analysis comparing districts with targeted digital infrastructure investment to control areas without such interventions showed that treated areas recorded higher employment growth rates and SME formation over the study period. These findings support the hypothesis that digital infrastructure has a causal effect on local economic development outcomes.

Table 7: Difference in Difference Analysis

Coefficient	Estimate	Std. Error	t-value	p-value
Intercept	~50.55	±0.58	87.29	<0.001
Treatment (Group)	~0.18	±0.82	0.22	0.825
Post (Time)	~0.55	±0.82	0.67	0.503
Treatment × Post	4.86	±1.16	4.20	<0.001

The interaction term (Treatment × Post) is the DiD estimator. It represents the causal effect of digital infrastructure interventions. The coefficient of ~4.86 is statistically significant ($p < 0.001$), indicating that the intervention increased the outcome (e.g., productivity or employment) by nearly 5 units in treated areas relative to control areas.

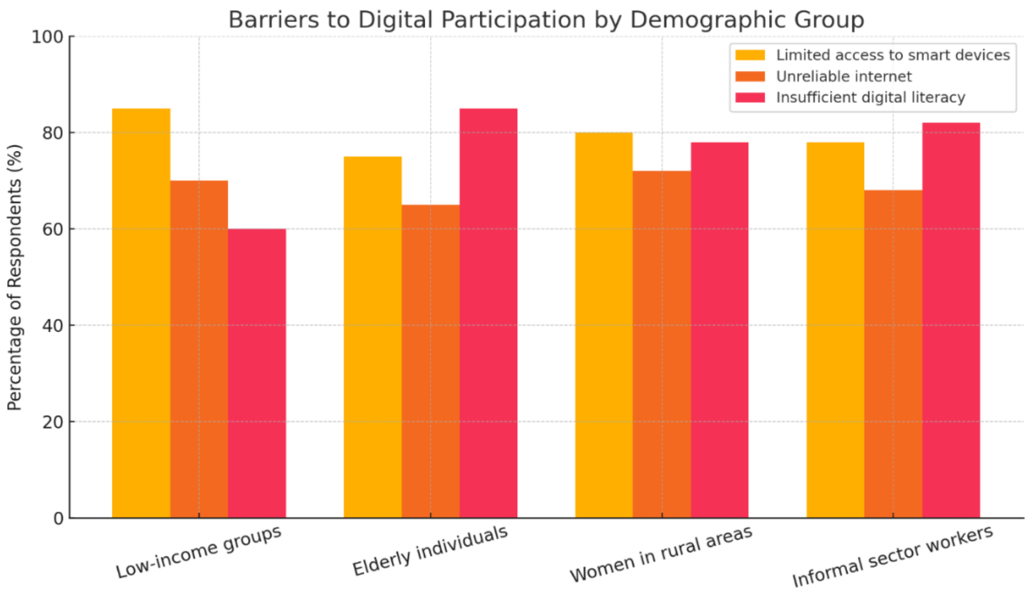


Figure 4: Social Inclusion and Digital Equity

The figure above visualizes the primary barriers to digital participation faced by various vulnerable groups in Bulawayo, based on survey responses. The findings reveal that low-income groups and women in rural areas are especially affected by limited access to smart devices, the elderly are hindered by illiteracy while the informal sector workers are hindered by both unreliable internet connectivity, and insufficient digital literacy. The research also reveals infrastructure deficits in electricity, broadband connectivity, gaps in policy and regulation, particularly around data protection, digital rights, and innovation funding.

5 Conclusion and Recommendations

5.1 Conclusion

Empirical research on the impact of digitalisation in African countries is limited. Furthermore, Africa is still facing legacy challenges that inhibit full scale adoption; therefore, the current moment offers a leapfrogging opportunity. Today's technologies indicate the scale and speed at which technology is transforming traditional socio-economic sectors (African Union, 2020). Our research contributes to this field by using an Autoregressive Distributed Lag (ARDL) model to examine the dynamic relationship between smart technology adoption, employment, and GDP growth in Bulawayo over the period 2003–2024. The results reveal a robust and statistically significant long-run effect of smart technology adoption on economic growth, with positive impacts emerging after a three-year lag. This confirms that digital transformation, while not immediately impactful, plays a pivotal role in enhancing productivity and stimulating sustained economic performance in the medium to long term.

The findings also point to a nuanced relationship between employment and economic growth. Specifically, the observed negative impact of employment two years prior suggests that job creation, if not accompanied by productivity improvements, may not contribute meaningfully to economic development. Conversely, the positive and marginally significant effect of employment at a three-year lag highlights the potential of quality employment to reinforce growth when it is strategically aligned with technological advancement and human capital development.

Overall, the study concludes that the integration of smart technologies offers a viable pathway for promoting sustainable and inclusive economic growth in Bulawayo. However, the benefits are contingent upon complementary policy measures that ensure widespread access, institutional readiness, and alignment with labor market dynamics.

5.2 Policy Recommendations

Based on the empirical evidence and theoretical insights, the following policy recommendations are proposed:

1. Invest in Long-Term Digital Infrastructure

Policymakers should prioritize sustained investments in digital infrastructure, including broadband internet, smart grids, and data-driven platforms, especially in underdeveloped urban and rural areas. Recognizing the time lag in returns, policies should adopt a medium- to long-term horizon for evaluating digital outcomes.

2. Promote Productive and Inclusive Employment

Employment creation should be accompanied by skill development programs that align with smart technology sectors such as ICT, precision agriculture, and green energy. Therefore, the growth effects of ICT can be maximised through a skilled labour force and an enabling ICT policy environment. As such, individual users would become drivers of digitalisation on the continent. This would incentivise firms to increase their use of technology to meet the demands of newly technology conscious consumers across Africa.

3. Support Digital Literacy and Innovation Adoption

To accelerate the diffusion of smart technologies, public-private partnerships should be formed to fund and deliver digital literacy training, particularly targeting youth, women, and informal sector workers. Innovation hubs and incubation centers should also be promoted to facilitate local technological development and entrepreneurship.

4. Enhance Policy Coherence and Institutional Capacity

Government agencies must streamline regulatory frameworks to support digital innovation while safeguarding data security, intellectual property, and consumer rights. Inter-agency coordination should be strengthened to ensure that digital transformation strategies are cross-cutting and inclusive.

5. Monitor and Evaluate Technology Impacts

Establish a robust monitoring and evaluation system to track the socio-economic impacts of digital interventions over time. This includes collecting disaggregated data on technology adoption, employment quality, and income generation to inform adaptive policy design.

In conclusion, this study contributes to the empirical understanding of how smart technologies influence economic growth in a developing urban-rural context. The evidence supports the call for strategic, inclusive, and forward-looking policy interventions that maximize the developmental potential of digital innovation while addressing structural barriers and inequalities in the economy.

Declaration of Competing Interests

The authors declare that they have no conflicting interests.

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Data Availability statement
The data used to support the findings of this study are available upon request, from the corresponding author.

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