DIGITAL ECONOMY AND TRADE: EVIDENCE FROM SOUTH AFRICA

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Abstract

Advances in Information and Communication Technology (ICT) have mitigated the physical distance as a trade barrier, making it easier to trade globally. Information and Communication Technology has become very important in today's globalisation era. As a result, the primary aim of this study is to analyse the influence of digital economy on trade in South Africa from 1990 to 2022. The study used Autoregressive Distributed Lags (ARDL) approach to examine the impact of population of individuals using internet, literacy rate, economic globalisation and foreign direct investment on the trade share. The results showed that population of individuals using internet have a positive and significance impact on trade share in the long run. Similarly, there was a positive and significance relationship between trade share and literacy rate, economic globalisation and foreign direct investment in the long run. Furthermore, the study reported that literacy rate, economic globalisation and foreign direct investment influence trade share positivity in the long run. The study recommend that policy makers should prioritise digital inclusion initiatives, which aims to increase the internet access in the rural areas and digital literacy to people who are not familiar with technology. By doing so, this will lead to a higher number of internet users, ultimately fostering a positive and significant on trade.

Keywords: ARDL, Digital economy, ICT, Trade and South Africa.

1. Introduction

The digital revolution has fundamentally transformed South Africa's trade landscape, with information and communications technology (ICT) significantly advancing economically 72% in 2023, representing 43.48 million users (DataPortal's Digital, 2023). This digital connectivity has enabled global business relationships, with e-commerce revenue share reaching 21.4% in 2021 (Statistics South Africa, 2022). As Choi (2010) noted, ICT has facilitated the unrestricted exchange of ideas and innovations, while Dettmer (2014) observed that digital technologies have effectively eliminated physical distance as a barrier to trade.

Despite substantial progress, South Africa continues to face a significant digital divide driven by socioeconomic factors. The country's high unemployment rate of 32.7% (Statistics South Africa, 2023) creates financial barriers to technology access, while geographic disparities between urban and rural areas limit connectivity. According to ICASA (2022), 63% of seniors cite "lack of knowledge" as their primary reason for not using the internet, highlighting generational gaps in digital literacy. Ngubane (2020) identified multiple factors contributing to this divide, including location, age, race, language, disability, and gender. This digital growth has created both opportunities and challenges for the nation's trade position. Despite increasing connectivity, South Africa continues to struggle with inadequate digital infrastructure, particularly in rural areas, creating barriers for businesses attempting to leverage technology for trade purposes.

For South Africa to fully capitalize on digital trade opportunities, significant investments in infrastructure and skills development are essential. Looking at the ongoing debate on global digital transformation, it is crucial to examine the correlation between digital economy and trade in South Africa. Multiple researchers, including Freund and Weinhold (2004) and Ozcan (2018), have confirmed that ICT adoption lowers market entry costs, reduces information delays, and improves planning efficiency for international trade. As Liu and Nath (2013) observed, ICT directly assists global trade of information-intensive services, while a functional digital economy facilitates efficient capital allocation and immediate access to foreign markets (Petersen, 2019). There has been varied results that contradict one another.

Some studies have shown that information and communications technology have a beneficial impact on trade (Abendin et al., 2022; and Sawadogo and Wandaogo, 2020), while other studies have found the opposite results (Mattes, Meinen, and Pavel, 2012). The primary objective of this study is to examine the impact of digital economy on trade in South Africa. This study seeks to add and contribute to the gap in literature on the effects of digital economy on trade in South Africa. To do so, the study uses Auto Regressive Distributed Lag (ARDL). Few researches have concentrated on the effects of digital economy on trade through Auto Regressive Distributed Lag (ARDL). Studies by Abendin et al. (2022), Epo et al. (2020) and Ozcan (2018) utilized gravity model. Therefore, the study seeks and aim to close the gap in terms of the variables and methods used.

The structure of the paper is as follows: The first section details the introduction. Section two focuses on literature review. Section three exhibits' data and methodology. The empirical results analysis discusses the empirical findings from the study. The last section concludes the study and provides recommendations.

2. Literature review

This section is categorised into two sub sections: theoretical and empirical literature. The first section analyses the theoretical literature that links digital economy and trade, while the empirical section critically reviews a few selected previous studies on digitalisation and trade.

2.1 Theoretical literature

Technological Gap Theory (Posner, 1961)

The technology gap model was developed by Posner in 1961 to explain how technological innovation drives international trade patterns. According to Posner, innovation creates temporary monopolies that generate trade even between countries with identical factor endowments. The model identifies three critical lags - international response, domestic response, and demand lag - that determine trade dynamics between nations. For digital economies, this theory explains how countries with less developed digital infrastructure struggle to compete internationally and highlights the digital divide between nations.

Several scholars have challenged the applicability of Posner's model in contemporary contexts. Krugman (1995) argues that the model oversimplifies innovation processes by treating technology as exogenous, failing to account for deliberate research and development investments and strategic innovation policies. Similarly, Dosi and Soete (1988) critique the model's assumption of homogeneous technological capabilities, noting that countries possess vastly different absorptive capacities that affect their ability to imitate technologies. Despite these critiques, some researchers have effectively used and tested Posner's theory, Castellacci (2008) demonstrated that technology gaps remain a significant determinant of trade flows, particularly between developed and developing nations.

The model shortcomings include that it does not provide a clear justification for either the technology or imitation gaps and it fails to explain why the technical gaps exist and how they get eliminated over time. This theory relates to the study as the study aims to investigate the relationship between digital economy and trade. The theory is very important in this study as it highlights the how a country with less developed digital infrastructure struggle to compete with other nations and explains the digital divide among nations. This theory states that there is a positive relationship between digital economy and trade. By addressing the technological gap, countries can enhance digital trade competitiveness. Therefore, thus study anticipates that there is a significant and positive relationship between digital economy and trade.

Product Cycle Theory (Vernon, 1966)

The product cycle model, proposed by Vernon in 1966 describes how an innovating country produces and exports a product before becoming an importer of the same product or a similar but differentiated variety of the same product. Vernon's theory describes how innovative products move through five stages: introduction, growth, maturity, saturation, and decline. Initially, developed countries introduce new products for domestic markets before exporting them. As products become standardised, production shifts to countries with lower costs. In the digital context, this theory applies to digital products, platforms, and infrastructure.

Storper (1985) strongly opposed this concept, arguing that it is too broad and did not take into account the specificities of industries as a required prism through which structural forces are refracted into specific outcome. Ernst and Kim (2002) criticise the theory's incapacity to explain reverse innovation, in which items produced for emerging markets are later introduced into industrialized countries. This challenges Vernon's key assumption that innovation originates in high-income countries. The shortcomings of the product-cycle model as applied in geography are linked to the insufficient conceptualisation of the firm, which is still common in the field. Vernon (1966) clarifies that being physically close to a market can facilitate the free flow of information.

The Product Cycle theory relates to this study because in the digital economy, the theory applies to digital product, platform and infrastructure. Digital innovation drives trade growth through new products while digital platforms facilitate trade reducing transaction costs. Therefore, we anticipate that there is a positive relationship between the digital economy and trade.

2.2 Empirical literature

Previous studies have analysed the relationship between digitalisation and trade in different countries. Kere and Zongo (2023) studied how digital technology affects businesses in Africa using the augmented gravity model. Data was collected from 48 countries in Sub-Saharan Africa (SSA) for the years 2000 and 2008. The results showed that using technology, especially the internet, increases exports while negatively impacting importation of basic goods and/or products. These results align with the Product Cycle Theory, which posits that as countries adopt and advance in technology, they shift from importing basic goods to producing and exporting more sophisticated products, thereby increasing exports and reducing reliance on imports.

Al-Badrany and Al-Din Al-Khatib (2023) investigated the relationship between digital economy development and international trade in Egypt using a Vector Error Correction Model (VECM) and Granger causality test on time-series data from 2005 to 2020. The study found a significant positive relationship between digital economy indicators and international trade These findings support the Technological Gap Theory, suggesting that digital economy development facilitates international trade and bridges the technology gap between countries.

Abendin et al., (2022), investigated how digital technology influenced trade in Africa. The study focused on trade within ECOWAS countries between 2000 and 2018. The study looked at how digital technology affects trade between two countries using a gravity model, generalised least squares (GLS), pooled ordinary least squares (POLS), and Poisson pseudo maximum likelihood (PPML). The results verified that trade between countries in the ECOWAS region benefited significantly from digital technology. Trade among ECOWAS member countries grows a lot as their economies become more digital. These results corroborate what Epo, and Nguenkwe, (2020). Specifically, the study demonstrated that trade within the ECOWAS region was significantly facilitated by information and communication technologies. These findings align with the principles of Transaction Cost Theory, which suggest that ICT reduces the costs associated with economic transactions. The idea focuses on reducing the costs of trading. Digital technology lowers transaction costs by making payments easier, improving how products are delivered, and providing better information about the market.

Sawadogo and Wandaogo (2020) conducted a study from 1995 to 2018 to investigate how mobile money services affect trade between 48 African countries. The research used Propensity Score Matching (PSM) method to verify that countries that used mobile money had a goods trade share of 0.6 percentage points higher in their GDP compared to countries that do not. Importantly for the food business, it was confirmed that using mobile money helps increase imports more than exports. Using mobile money services improves trade between African countries by making the payment process faster and easier.

Zhang et al., (2022) examined how the Internet has altered urban export trade and its diversity. Using panel data with a fixed effect model from 2005 to 2019, this study looked at 285 prefecture-level cities in China. The research study used a gravity model and concluded that the impact that digital economy promotion had on city export growth varied significantly depending on the city's location, with a greater impact evident in western and north-eastern cities that are relatively remote. Cities in the third and fourth tiers, characterised by slower economic growth and technological improvement, have nonetheless made substantial contributions to the promotion of the digital economy's export growth. Therefore, it is crucial that China spend more on infrastructural investment for the digital economy while paying critical attention to the differences in which different cities develop. China should fund basic IT research and development to promote the quality expansion of its digital economy's foreign trade. The gap that this study addresses is the limited number of research studies focusing specifically on South Africa using the ARDL (Autoregressive Distributed Lag) model. While most existing studies rely on panel data across multiple countries, this study distinguishes itself by employing time series data to provide a more in-depth, country-specific analysis.

3. Methodology

To investigate the impact of digital economy on trade in South Africa, the study adopts a model used by Al-Badrany and Al-Din Al-Khatib (2023) to examine impact of digital economy on international trade in Egypt. The adopted model is expressed as follows:

$$\gamma = f\ (X_1, X_2, X_3, X_4)\ ei \quad \ldots\ldots (1)$$

Where:
γ is the ratio of total trade to GDP,
X_1 is the economic globalisation,
X_2 is the foreign direct investment,
X_3 is the number of resident-registered patents,
X_4 is human development and ei is the random variable, which is made up of all factors that the model does not show or that does not account for and that, if applied, would have an impact on the model.

The modified mathematical model and econometric expression for South Africa to analyse the impact of digital economy on trade is expressed as follows:

$$TRD\_SHR_t = \beta_0 + \beta_1 POP\_INT_t + \beta_2 LIT\_RAT_t + \beta_3 ECO\_GLO_t + \beta_4 FDI_t + \varepsilon_t \quad \ldots\ldots (2)$$

Where:
subscript "t" is time,
α_t is different intercept for each year,
β_1 - β_5 is the slope of the parameters,
ε_t is the error term,
TRD_SHR is trade share which is the dependent variable,

POP_INT_t is the population for individuals using internet as a proxy for ICT use,
LIT_RAT_t is the literacy rate as a proxy for ICT skills,
ECO_GLO_t is the economic globalisation, and
FDI_t is the Foreign Direct Investment.

Changes were made by removing and adding some variables. The total ratio of trade to GDP, human developments and number of residents registered patents were removed from the adopted model to avoid multicollinearity that can occur by having many independent variables because two variables (population of individuals using internet and literacy rate) were added to the model. The removed variables do not have statistically significant effects on the outcome of the study and the variables do not align with the study's objective and hypothesis. The motivation for adding more variables is that the new variables serve as a proxy for digital economy. The study employs the logarithm transformation of the variables below:

$$LTRD\_SHR_t = \beta_0 + \beta_1 LPOP\_INT_t + \beta_2 LLIT\_RAT_t + \beta_3 LECO\_GLO_t + \beta_4 LFDI_t + \varepsilon_t \quad (3)$$

The study employs yearly time series data from 1990 to 2022 with 32 observations. The data is obtained from the World bank and African Development Bank. Econometric programme Eviews 14 is used for all the empirical estimations.

This study utilises Auto Regressive Distributed Lag (ARDL) to examine the impact of digital economy on trade in South Africa. Pesaran and Shin (1999) created the ARDL model. This study chose to use the ARDL model because it is superior to small sample qualities compared to the Granger (1969) procedures and Johansen (1991) maximum probability reduced rank. The ARDL coefficients in this approach are not restricted and the long-run equilibrium relationship does not determine the dynamics in the short run (Mpofu, 2013). The following equation presents the ARDL model to be estimated in determining the effect of digital economy on trade in South Africa:

$$TRD\_SHR_t = y_o + \sum_{i=1}^{n1} y_{1i}\ \Delta\ INT\_POP_{t-1} + \sum_{i=1}^{n2} y2_i\ \Delta\ LIT\_RAT_{t-1} + \sum_{i=1}^{n3} y_{3i}\ \Delta\ ECO\_GLO_{t-1} + \sum_{i=1}^{n4} y_{4\,i} + \Delta FDI_{t-1} + y_7 TRD\_SHR_{t-1} + y_8 POP\_INT_{t-1} + y_9 LIT\_RAT_{t-1} + y_{10} ECO\_GLO_{t-1} + y_{11} FDI_{t-1} \quad (4)$$

The estimation procedures are as follows:

Descriptive statistics: descriptive statistics make the data more meaningful by describing, showing, and summarising it in a way that the patterns appear.

Formal unit root test: Augmented Dickey Fuller and Phillips Perron unit root tests are employed to test the presence of unit root for all the variables in this study.

ARDL Bounds cointegration test: the bounds cointegration test is employed to assess the existence of a long-term relationship between the variables. The test comprises the subsequent hypotheses: H0: There is no long run relationship. H1: There is a long run relationship. We reject the null hypothesis of no long run relationship of the F-statistics is greater than the upper bound or less than the lower bound.

Regression analysis (Long-run analysis and Error Correction Model): regression analysis is employed to analyse the link between a dependent variable and independent variable if there is cointegration among the variables. Two types of regression analyses are run in this study, long-run analysis and Error Correction Model. The long run analysis is used to analyse the long run relationship between the variables. The ECM model is utilised to analyse the short-run relationship between variables. The ECT is a coefficient that must possess a negative value and be statistically significant to demonstrate a long-term relationship between the dependent and independent variables; when the ECT coefficient equals zero, it indicates the absence of cointegration among the variables. The ECM equation is illustrated as follows:

$$\Delta Y_t = \alpha + \beta_1 \Delta X_t + \beta_2 (Y_{t-1} - rX_{t-1}) + \epsilon_t \quad (5)$$

Where:
ΔY_t denotes the change in the dependent variable Y at time,
ΔX_t denotes the change in independent variables at time,
r is the coefficient of error correction term, and
Δ represents the first difference operator.

Granger Causality Test: this test is conducted to establish causality between variables and assess the ability of one variable to influence the other. The Granger Causality Test consists of two assumptions. The null hypothesis is rejected if the p-value is below the significance level of 0.05: H0: xt does not cause yt. H1: xt does cause yt

The Granger Causality test is carried out using the following equations:

$$y_t = a_1 + \sum_{i=1}^{n} \beta i \, x_{t-i} + \sum_{j-1}^{m} y_j \; y_{t-1} + e_{1t} \quad (6)$$

$$x_t = a_2 + \sum_{i=1}^{n} \theta i \, x_{t-i} + \sum_{j-1}^{m} y_j \; \delta j_{t-1} + e_{2t} \quad (7)$$

- *Residual diagnostic tests*

Diagnostics tests are conducted to verify the accuracy of the model's specification. The study employs a series of diagnostic tests which includes normality tests, serial correlation, heteroscedasticity test and Ramsey Regression Error Specification Test.

4. Results and Discussion

The first step in running ARDL is to assess the time series characteristics of all variables in the model. Table 1 present the descriptive statistics results for the variables.

The descriptive statistics reveal diverse distribution patterns across the variables. Trade share and literacy rate exhibit platykurtic distributions with negative skewness, suggesting fewer extreme values and a left-skewed data pattern, while their similar mean and median values indicate relatively symmetric distributions. In contrast, Foreign Direct Investment displays leptokurtic characteristics with heavier tails, indicating more extreme values in the dataset. Economic globalisation and internet usage population show mesokurtic distributions, aligning with normal distribution patterns, though internet usage has high standard deviation values, indicating greater data dispersion. The clustered data (low standard deviation) for trade share, literacy rate, and economic globalization suggests more consistent measurements, while the widely dispersed data for internet usage and FDI points to greater variability, reflecting the dynamic and evolving nature of these factors in South Africa's developing digital economy.

Table 1 − Descriptive statistics results

	LTRD_SHR	LPOP_INT	LLIT_RAT	LECO_GLO	LFDI
Mean	3.883261	1.882773	4.499771	3.892247	21.24756
Median	3.920112	2.087580	4.454672	3.992702	21.51866
Maximum	4.189269	4.280969	4.716729	4.041027	24.42848
Minimum	3.535768	-4.321226	4.336146	3.413922	15.02686
Std.Dev	0.170319	2.227380	0.134029	0.198188	1.878050
Skewness	-0.537428	-1.123113	0.577641	-1.288661	-1.634479
Kurtosis	2.415308	3.639911	1.822334	3.147814	28.25987
Jarque B	1.933857	7.046062	3.515365	8.608227	28.25987
P(JB)	0.380249	0.029510	0.172444	0.013513	0.000001
Sum	120.3811	58.3659	139.4929	120.6597	658.6744
Sum Sq.Dev	0.870254	155.5938	0.538912	1.178351	105.8121
Observations	31	31	31	31	31

Source: compiled by the author, using EViews 14 (2025)

Formal unit root test

After descriptive statistics, formal unit root tests are conducted, and results are presented in Table 2a and 2b.

Table 2a − ADF and PP results in levels

Variables	Model	ADF critical values at level form		PP critical values at level form		Critical values		
		t-statistics	P- value	t-statistics	Probability value	1%	5%	10%
LTRD_SHR	Intercept	-1.2485	0.6408	-0.5587	0.8662	-3.6537	-2.9571	-2.6174
	Int. & trend	-2.7981	0.2082	-2.7243	0.2342	-4.2731	-3.5577	-3.2123
	None	1.0361	0.9175	3.8664	0.9999	-2.6392	-1.9516	-1.6105
LPOP_INT	Intercept	3.2000	0.0299**	-5.9062	0.0000***	-3.6701	-2.9639	-2.6210
	Int. & trend	-3.3544	0.0770*	-4.3751	0.0081***	-4.2967	-3.5683	-3.2183
	None	-0.2346	0.5933	-0.8153	0.3546	-2.6443	-1.9524	-1.6102
LLIT_RAT	Intercept	-0.1424	0.9358	-0.3838	0.9004	-3.6616	-2.9604	-2.6191
	Int. & trend	-1.8235	0.6689	-1.1935	0.8950	-4.2967	-3.5683	-3.2183
	None	0.8556	0.8900	1.3496	0.9523	-2.6416	1.9520	-1.6104
LECO_GLO	Intercept	-2.0681	0.2581	-2.0526	0.2642	3.6616	-2.9604	-2.6191
	Int. & trend	-0.9686	0.9346	-0.9271	0.9403	-4,2845	-3.5628	-3.2152
	None	1.3145	0.9490	1.4381	0.9595	-2.6416	-1,9520	-1.6104
LFDI	Intercept	-2.7358	0.0792*	-2.4950	0.1206	-3.6537	2,9571	-2.6174
	Int. & trend	-3.8252	0.0275**	-3.7826	0.0308**	-4.2732	-3,5577	-3,2123
	None	0.5464	0.8286	1.6361	0.9725	-2.6416	-1,9520	1.6104

***statistically significant at 1%** statistically significant at 5%* Statistically significant at 10%

Source: compiled by the author using Eviews 14 (2025)

Table 2a shows that Augmented Dicker Fuller and Phillips Perron results in level form. All variables are tested three ways (a) intercept, (b) trend and intercept and (c) none. The null hypothesis of no stationary is rejected at one, five and ten percent significance level. Results indicate that all the variables apart form POP_INT (Population for individuals using internet) are non-stationary in levels. Since almost all variables were non-stationary in levels, the next step is to test for unit root after first differencing. Table 2b presents unit root results after first differencing.

Table 2b − ADF and PP results at first differencing

Variables	Model	ADF critical values at first difference		PP critical values at first difference		Critical values		
		t-statistics	Probability value	t-statistics	Probability value	1%	5%	10%
D(LTRD_SHR)	Intercept	-5.7487	0.0000***	-9.7658	0.0000***	-3.6616	-2.9604	-2.6191
	Int. & trend	-4.8746	0.0029***	-10.6229	0.0000***	-4.3393	-3.5875	-3.2292
	None	-5.5398	0.0000***	-5.5526	0.0000***	-2,6416	-1,9520	1,6104
D(LPOP_INT)	Intercept	-2.8659	0.0614	-2.7719	0.0744*	3.6701	-2,9639	-2.6210
	Int. & trend	-3.3570	0.0766*	-3.2426	0.0955*	-4.2967	-3.5683	-3.2183
	None	-2.7503	0.0077**	-2.8614	0.0058***	-2.6443	-1.9524	1.6102
D(LLIT_RAT)	Intercept	-4.1665	0.0028***	-2.1682	0.0028***	3.6616	-2.9604	-2.6191
	Int. & trend	-4.4906	0.0061***	-4.4945	0.0061***	-4.2845	-3.5628	-3.2152
	None	-4.1175	0.0002***	4.1137	0.0002***	-2,6416	-9.9520	-1.6105
D (LECO_GLO)	Intercept	-4.0140	0.0042***	-4.0525	0.0038***	-3.6616	-2.9604	-2.6190
	Int. & trend	-4.6506	0.0042***	-4.8728	0.0024***	-4.3239	-3.5806	3.2252
	None	-3.6789	0.0006***	-3.6789	0.0006***	-2.6416	1.9529	1.6104
D(LFDI)	Intercept	-7.8124	0.0000***	-19.0620	0.0001***	-3.6616	-2.9604	-2.6190
	Int. & trend	-7.6760	0.0000***	-19.1735	0.0000***	-4.2845	-3.5628	-3.2152
	None	-7.8571	0.0000***	-9.9918	0.0000***	-2.6416	-1.9520	1.6204

***statistically significant at 1%** statistically significant at 5%* Statistically significant at 10%
Source: compiled by the author using EViews 14 (2025)

Table 2b shows the Augmented Dicker Fuller and Phillips Perron results after first differencing. The null hypothesis of no stationary is rejected at one, five and ten percent significance level, meaning that all variables become stationary after first differencing. The next step is test for cointegration between variables

ARDL Bounds cointegration test results

Bounds cointegration test is used to examine if there is a long-run relationship among the variables. The study employs the bounds test of Autoregressive Distributed Lag (ARDL) to test for cointegration. Table 3 illustrate the of bounds test results.

Table 3 − ARDL Bounds cointegration test results

Test statistic	Value	
F statistic	5.480827	
Critical values of bounds for F-statistic		
Significance level	I(0) bounds	I(1) bounds
10%	2.2	3.09
5%	2.56	3.49
2.5%	2.88	3.87
1%	3.29	4.37

Source: compiled by the author using EViews 14 (2025)

Table 3 presents the bounds cointegration results. The F-statistic of 5.480827 exceeds the upper bound critical values at the 10%, 5%, 2.5%, and 1% significance levels. Consequently, we reject the null hypothesis of no long-run association, indicating the existence of cointegration among the variables. Given the established long-run relationship among the variables, long-run regression run

4.1 Long run analysis results

Following the previous part, the model was designed to ascertain the presence of a long-term association between the variables. The model indicated that there is cointegration among the variables. Long-run regression is employed to ascertain the presence of a long-term association among the variables. The estimates of the long-run relationship for the ARDL model are presented in Table 4. Table 4 present the long-run ARDL estimation for digital economy and trade from 1990 to 2022 in South Africa.

Table 4 − Long run analysis results

Dependent variable: LTRD_SHR Number of size after sample adjustment: 1993 – 2022 Observations included: 23				
Variable	Coefficients	Standard error	T-statistics	Probability
LTRD_SHR(-1)	-0.432001	0.250048	1.727670	0.1147
LPOP_INT	0.021040	0.009834	2.139548	0.0581*
LLIT_RAT	0.516493	0.169271	3.051283	0.0122**
LECO_GLO	0.030828	0.009795	3.147414	0.0104**
LFDI	0.052086	0.014646	3.556288	0.0052***
C	3.563965	1.605023	2.220507	0.0507*

Source: compiled by the author using EViews 14 (2025)

The analysis of the long-run ARDL model reveals significant positive relationships between trade share and several key factors in South Africa. Internet usage demonstrates a positive impact, with a 1% increase leading to a 2.1% increase in trade share by enhancing e-commerce and global market access. Literacy rate shows the strongest effect, where a

1% increase results in a substantial 51.6% increase in trade share through improved productivity and trade competitiveness. Economic globalization also positively influences trade share, with a 1% increase generating a 3.1% increase by advancing technological integration and reducing trade costs. Similarly, Foreign Direct Investment shows a significant positive relationship, with a 1% increase yielding a 5.2% increase in trade share through technology transfer and economic growth stimulation. These findings align with established economic frameworks including the imitation lag hypothesis and product cycle theory. Having established these long-run relationships, the study proceeds with an Error Correction Model to examine short-run fluctuations.

Error Correction Model results

The error correction model in this study is used to determine the short-run impact of digital economy on trade in South Africa. Table 5 illustrates the short run regression results.

Table 5 − Short run regression results

Dependent variable: LTRD_SHR Number of size after sample adjustment: 1993 – 2022 Observations included: 23				
Variable	Coefficients	Standard error	T-statistics	Probability
D(LTRD_SHR(-1))	-1.515103	0.200205	-7.567742	0.0006***
D(LTRD_SHR(-2))	-0.518666	0.160206	-3.237497	0.0230**
D(POP_INT)	-0.319676	0.054958	-5.816768	0.0021**
D(POP_INT(-1))	-0.163130	0.062207	-4.599650	0.0058*
D(POP_INT(-2))	-0.297505	0.019014	-8.579660	0.0004***
D(LLIT_RAT)	2.718159	0.081683	-3.642198	0.0149
D(ECO_GLO(-1))	3.414097	0.261452	10.39640	0.0003***
D(ECO_GLO(-2))	1.316581	0.065370	8.950920	0.0061**
D(FDI)	0.069036	0.031011	2.226180	0.0765*
D(FDI(-1))	-0.171089	0.065370	-2.617259	0.0473*
D(FDI(-2))	-0.27979	0.051618	-5.420535	0.0029**
CointEq(-1)*	-0.814460	0.102305	7.961082	0.0005***
R- Squared: 0.970648 Adjusted R-Squared: 0.935426				

***statistically significant at 1%** statistically significant at 5%* Statistically significant at 10%
Source: compiled by the author using EViews 14 (2025)

Table 5 presents the error correction results. In the short run, the variables have different coefficients signs. The error correction coefficient signifies the rate of convergence. The coefficient linked to the error term is negative and statistically significant at the one percent level. This outcome demonstrates that the short-term imbalances present in the model have been rectified in the long term, signifying that the economy will revert to a stable condition. The convergence speed of 0.8144 indicates that the model progresses at a rate of 81.44 percent towards equilibrium.

Granger Causality Test results

The Granger causality relationship among the five variables under consideration is shown in this section. The null hypothesis states that xt do not Granger cause yt. meanwhile, the alternate theory states that Granger causes xt. This test determines the causal relationship between the variables, and it can also be utilised to ascertain the direction of causation among other variables. Table 6 shows the Granger causality results.

Table 6 − Granger Causality Results

Null hypothesis	Obs	F-stats	P-value	Decision
LPOP_INT does not granger cause LTRD_SHR LTRD_SHR does not granger cause LPOP_INT	30	0.44256 9.68236	0.7248 0.0003***	No causality Causality
LLIT_RAT does not granger cause LTRD_SHR LTRD_SHR does not granger cause LLIT_RAT	30	0.37986 1.20056	0.7684 0.3317	No causality No causality
LECO_GLO does not granger cause LTRD_SHR LTRD_SHR does not granger cause LECO_GLO	30	1.75688 0.20643	0.1835 0.8909	No causality No causality
LFDI does not granger cause LTRD_SHR LTRD_SHR does not granger cause LFDI	30	3.93507 0.93633	0.0211** 0.4392	causality No causality
LLIT_RAT does not granger cause LPOP_INT LPOP_INT does not granger cause LLIT_RAT	30	0.05724 3.84786	0.9816 0.0228**	No causality Causality
LECO_GLO does not granger cause LPOP_INT LPOP_INT does not granger cause LECO_GLO	30	0.15476 0.10861	0.3483 0.9542	No causality No causality
LFDI does not granger cause LPOP_INT LPOP_INT does not granger cause LFDI	30	0.65866 0.41758	0.5858 0.7421	No causality No causality
LECO_GLO does not granger cause LLIT_RAT LLIT_RAT does not granger cause LECO_GLO	30	2.41145 0.10800	0.0928* 0.9546	causality No causality
LFDI does not granger cause LLIT_RAT LLIT_RAT does not granger cause LFDI	30	1.32820 0.50062	0.2895 0.6856	No causality No causality
LFDI does not granger cause LECO_GLO LECO_GLO does not granger cause LFDI	30	3.44571 0.67518	0.0334** 0.5761	causality No causality

***statistically significant at 1%** statistically significant at 5%* Statistically significant at 10%
Source: compiled by the author using EViews 14 (2025)

The Granger causality tests reveal important directional relationships between variables. There exists a unidirectional causal relationship from trade share to population of individuals using internet (p=0.0003), but not vice versa (p=0.7248), suggesting that changes in trade share can predict alterations in internet usage. This finding aligns with Lee et al. (2024) who found similar causality in Asian economies, and Ngwen et al. (2019) who demonstrated internet's positive impact on trade share. Similarly, a unidirectional causal relationship exists from Foreign Direct Investment to trade share (p=0.0211), while trade share does not Granger cause FDI (p=0.4392). These results are consistent with studies by Ahmed and Hossain (2017) and Hossain and Ahmed (2018) who found positive relationships between ICT, trade openness, and FDI. However, no causal relationships were found between trade share and literacy rate (p=0.7684, p=0.3317) or between trade share and economic globalization (p=0.1835, p=0.8909), indicating these variables do not predict changes in one another at statistically significant levels.

Residual Diagnostic test results

This section discusses the diagnostic testing performed on the residuals. The diagnostic and stability tests assess the accurate specification of a model and evaluate its goodness of fit. The normality test, the heteroskedasticity test, and the stability test are the tests that are carried out. Table 7 represents the residual diagnostic test performed in the study.

Table 7 − Residual diagnostic test results

Test	Jarque-Bera (JB)	Langrage Multiplier (LM)	White test (chi-square)	Ramsey Reset Specification
Null hypothesis	Residuals are normally distributed	No serial correlation	No heteroskedasticity	No misspecification
F-statistics	5.818809	0.548733	0.36755	3.112103
Prob value	0.066576	0.7018	0.9683	0.0621
Conclusion	Fail to reject the null hypothesis	Fail reject the null hypothesis	Fail to reject the null hypothesis	Fail to reject the null hypothesis

Source: compiled by the author using EViews 14 (2025)

Diagnostic tests are performed to evaluate how well the model fits the data. All residual diagnostic tests demonstrate that the null hypotheses are not rejected at the one, five, and ten percent ten percent significance levels, signifying that the residuals exhibit no serial correlation, heteroscedasticity, are normally distributed, and the model demonstrate no misspecification.

5. Conclusions

This study accomplished its primary purpose of examining the impact of the digital economy on trade in South Africa for the period 1990 to 2022. The study employs Autoregressive Distributed Lag (ARDL). The authors ran a series of tests on the relationship between the variables. Firstly, Descriptive statistics test was carried out, followed by unit root test. Variables in the model become stationary after first difference. The results from the ARDL bounds cointegration test revealed the presence of long run relationship between the variables. As a results ARDL long run test and Error Correction Model were carried out and the following results are reported:

- Population of individuals using internet has positive coefficient. As a result, there is a positive relationship between trade share and population of individuals using internet in the long run. In addition, there is a positive and significant long-run relationship between trade share and literacy rate, economic globalisation and foreign direct investment.
- The short-term imbalances present in the model have been rectified in the long term, signifying that the economy will revert to a stable condition. The convergence

speed of 0.8144 indicates that the model progresses at a rate of 81.44 percent towards equilibrium.

- There exists a unidirectional causal relationship from trade share to population of individuals using internet, Similarly, a unidirectional causal relationship exists from Foreign Direct Investment to trade share. However, no causal relationships were found between trade share and literacy rate or between trade share and economic globalization.
- All residual diagnostic tests demonstrate that there is no serial correlation, heteroscedasticity, residuals are normally distributed, and the model demonstrates no misspecification.

Recommendations

Based on the results, the study suggests that policy makers should promote digital inclusion, encourage internet penetration and digital literacy to increase the population of internet users, which has a positive influence on trade. Policymakers should prioritise the development of Internet infrastructure and the use of internet to mitigate needless trade barriers. Policies that promote and support the adoption and deployment of internet users would significantly enhance trade. Additionally, the country must enhance its economic connections with nations possessing substantial ICT resources.

It is essential to improve the digital skills of individuals or organisations to facilitate their adaptation to the digital revolution and advancements in modern technologies. The study recommend that policy makers should invest in education. The necessity to manage the digital economy is anticipated to play a crucial role in all facets of life in the future. Establish the necessary infrastructure for trained and highly skilled workers, as they represent a significant transformation that will impact international trade amongst globalisation, the digital economy, and the swift advancements in technology and information. Attracting foreign direct investment, particularly in the technology and information sectors, due to its beneficial impact on the economy.

One of the key limitations of this study is the necessity to extrapolate data for literacy rate in the model. Due to incomplete data, it was necessary to estimate values using the linear interpolation. Every effort was made to ensure the accuracy and reliability of the extrapolated data. Furthermore, data on Foreign Direct Investment was unavailable in the local currency; therefore, it was expressed in US dollars.

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