Global Journal of Economic and Finance Research

e-ISSN: 3050-5348
p-ISSN: 3050-533X

Vol. 02(05): 308-322, May 2025
Home Page: https://gjefr.com/index.php/gjefr

The Role of Artificial Intelligence in Digital Trade and Its Impact on Economic Growth in Ethiopia: An Empirical Time Series Analysis

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KEYWORDS: Artificial Intelligence, Economic Growth, Digital economy.

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Publication Date: 15 May-2025
DOI: 10.55677/GJEFR/05-2025-Vol02E5

ABSTRACT

This study investigates the role of artificial intelligence (AI) in facilitating digital trade and its impact on economic growth in Ethiopia through an empirical time series analysis. Leveraging data from 1992 to 2023 and employing a Vector Error Correction Model (VECM), the research examines the dynamic relationships between GDP growth and key determinants of digital trade, including internet penetration, ICT infrastructure, digital trade activity, and the trade index. The findings reveal a significant long-term relationship between GDP growth and these determinants, with internet penetration and ICT infrastructure playing pivotal roles in fostering economic development. Additionally, the trade index and digital trade activity are identified as critical in advancing Ethiopia's integration into the global digital economy. The study highlights the transformative potential of AI in digital trade by improving efficiency, accessibility, and market competitiveness. However, it identifies gaps in Ethiopia's adoption of AI, which limits the country's ability to fully capitalize on digital trade opportunities. By offering actionable recommendations for policymakers, this research underscores the need for strategic investments in AI and ICT infrastructure to harness the benefits of digital trade. Such efforts are crucial for driving sustainable economic growth and positioning Ethiopia as a competitive player in the global digital economy.

INTRODUCTION

Digital trade has emerged as a significant driver of economic growth globally, transforming the way countries conduct business by reducing transaction costs, expanding market access, and fostering innovation. The role of artificial intelligence (AI) in optimizing trade processes, enhancing decision-making, and delivering personalized services is increasingly recognized as crucial in the modern digital economy (OECD, 2021). AI applications such as predictive analytics, intelligent automation, and customer relationship management enable firms to adapt to the dynamic nature of global commerce, providing them with the tools to enhance productivity and market reach (McKinsey Global Institute, 2018). In developed economies, the integration of AI into digital trade has had a profound impact on boosting productivity and expanding market reach (World Economic Forum, 2020). As a result, countries with advanced digital infrastructure are able to maximize the potential of AI to enhance their trade capabilities, strengthen global competitiveness, and contribute significantly to their economic growth. Ethiopia, as part of its digital transformation agenda, has acknowledged the importance of technology, particularly AI, in modernizing its economy. The National Digital Strategy of Ethiopia (2020–2025) outlines the goal of leveraging digital trade for inclusive growth. However, the integration of AI into Ethiopia's trade ecosystem faces several barriers, including low technological infrastructure, a limited skilled workforce, and regulatory challenges that hinder the rapid adoption of AI solutions (Ministry of Innovation and Technology, Ethiopia, 2020). Despite the recognition of AI's potential to revolutionize trade, Ethiopia has lagged in adopting AI-driven solutions compared to more developed economies. Existing studies largely focus on developed countries, leaving a significant gap in empirical research on how AI can transform the digital trade sector in emerging economies like Ethiopia.

The shift towards digital trade, powered by advancements in AI, holds transformative potential for Ethiopia's economy. Digital trade enables the country to reduce its reliance on traditional trade methods by providing faster, more efficient platforms for exchanging goods and services. Moreover, Ethiopia can leverage digital trade to enhance market access, reduce transaction costs, and foster innovation. By promoting e-commerce, AI-powered tools, and research and development (R&D) incentives, Ethiopia can unlock the benefits of digital trade for sustainable economic development (Sarangi & Pradhan, 2020). However, for Ethiopia to fully capitalize on these opportunities, it needs to overcome the challenges associated with limited internet penetration, inadequate digital literacy, and insufficient ICT infrastructure. The government has recognized the critical role of ICT in fostering economic growth and reducing poverty, with ICT supported development projects yielding better outcomes in other regions, particularly in East Africa (Lixi & Dahan, 2014). In Ethiopia, the development of ICT infrastructure is seen as integral to achieving the country's socioeconomic goals, and there is an increasing focus on utilizing the most advanced technologies to boost economic development (Lixi & Dahan, 2014).

Export diversification plays an essential role in driving economic growth, with a positive relationship between economic globalization, trade diversification, and GDP growth (Gözgör & Can, 2017). Diversifying exports helps economies reduce their dependence on a narrow set of products or markets, thereby stabilizing their growth prospects. For developing nations like Ethiopia, increasing the export of new goods and services is a critical strategy for enhancing economic development (Rondeau & Roudaut, 2014). The expansion of trade diversification is particularly beneficial when accompanied by financial system expansion and capital accumulation. However, in Ethiopia, challenges remain in achieving sustainable economic growth, including low productivity, insufficient trade diversification, and limited global integration (Sarin, 2022). While Ethiopia's export diversification has positively impacted its GDP growth, the country still faces hurdles such as limited export diversification, low digital literacy, and insufficient infrastructure (Melkamu, 2015). Despite the significant global shift toward digital trade, Ethiopia's adoption of AI-driven solutions for trade optimization remains in its early stages. The country faces challenges such as insufficient digital infrastructure, regulatory hurdles, and low adoption rates of AI technologies in its trade sector (UNCTAD, 2022). The literature largely focuses on developed economies, with limited empirical research on how AI can impact digital trade in emerging economies like Ethiopia. This research gap limits the ability of policymakers and businesses to harness the full potential of AI in Ethiopia's digital trade ecosystem. To address these challenges, empirical research is needed to explore how AI can be effectively integrated into Ethiopia's trade framework, particularly in the face of resource constraints and rapidly evolving global trade dynamics.

AI has been shown to enhance trade efficiency, reduce costs, and expand market access in advanced economies (Manyika et al., 2017). In Ethiopia, AI can help optimize trade processes by automating tasks such as customs clearance, supply chain management, and customer service. Additionally, AI can provide valuable insights into market trends, consumer behavior, and demand forecasting, enabling businesses to make data-driven decisions that improve their competitiveness in international markets. Furthermore, AI-powered tools can help Ethiopian businesses access new markets by reducing language barriers, improving logistics, and streamlining payment systems, all of which can enhance Ethiopia's integration into the global digital economy. The impact of digital trade, ICT infrastructure development, internet penetration, and trade diversification on Ethiopia's economic growth is closely intertwined. As digital trade expands, it creates new opportunities for economic diversification, which can stabilize Ethiopia's economy and reduce its dependence on a few key exports. Investments in ICT infrastructure and increased internet penetration are crucial for enabling digital trade and improving access to global markets. However, these factors need to be supported by policies that foster digital literacy, improve internet connectivity, and encourage innovation in digital services. AI plays a central role in optimizing these trade variables by automating tasks, improving decision-making, and enhancing the overall efficiency of trade operations. By leveraging AI, Ethiopia can enhance the effectiveness of its digital trade sector and accelerate its economic growth.

The general objective of this study is to examine the role of AI in facilitating digital trade and its impact on economic growth in Ethiopia. Specific objectives include analyzing the extent of AI adoption in Ethiopia's digital trade sector, assessing the relationship between economic growth and key trade-related variables, and evaluating the impact of digital trade, ICT infrastructure, internet penetration, and trade diversification on Ethiopia's economic growth. The study also aims to evaluate how AI affects the effectiveness of these trade variables in driving Ethiopia's economic growth. The research hypothesizes that AI integration, trade diversification, ICT infrastructure, and internet penetration have significant impacts on Ethiopia's GDP growth rate. The findings of this study will provide valuable insights for policymakers and businesses in Ethiopia, offering recommendations for optimizing AI integration, addressing infrastructure gaps, and leveraging digital trade to enhance economic development. This study will contribute to the growing body of literature on AI in digital trade, particularly in the context of emerging economies. It will help bridge the knowledge gap on how AI can be integrated into Ethiopia's trade ecosystem, providing actionable recommendations for policymakers to foster a digital economy. The results of the study will also provide a foundation for future research on AI and digital trade in other developing countries, helping them navigate the challenges and opportunities presented by the global digital economy.

LITERATURE REVIEW

The acceleration of global commerce in the latter half of the 20th century has led to significant changes in trade patterns, which were previously understood through traditional trade theories based on perfect competition, comparative advantage, and consistent returns to scale. According to Krugman (1980), the global trade landscape shifted as countries moved away from the classical notions outlined by Adam Smith and the Heckscher-Ohlin Samuelson (HOS) model. These theories, which advocated for countries to specialize in industries where they had a comparative advantage, no longer entirely reflect the contemporary dynamics of global trade. Traditional models posited that economic growth and development could be driven by the specialization of nations in particular goods, based on their factor endowments, but recent findings suggest that countries tend to diversify their exports and production as they grow (Sannassee, 2014). This diversification is likely due to the broader, more complex nature of global trade today, which is influenced by factors such as technological advancement, shifts in consumer demands, and the nature of global value chains. Trade's impact on economic growth is well-established, and it has been shown that internet use significantly affects trade activity. The positive relationship between internet use, trade openness, and economic growth is supported by empirical studies using simultaneous equations models, which highlight the contribution of internet adoption to trade activities, particularly in non-high-income countries (Meijers, 2014). The internet has been pivotal in enhancing the openness of economies and facilitating trade by connecting markets and reducing transaction costs, especially in developing nations. This digital transformation has been supported by the expansion of ICT infrastructure, which has both direct and indirect effects on economic growth. The direct impact of ICT is reflected in increased productivity through the efficient use of technology, while the indirect impact stems from externalities, such as job creation, revenue generation, lower transaction costs, and the stimulation of knowledge creation and investment. These positive externalities have been crucial in fostering economic growth, as evidenced by studies on the global diffusion of ICT technologies (Khan & Haneklaus, 2023).

The Heckscher-Ohlin (HOS) model remains one of the most influential frameworks in understanding comparative advantage and trade patterns, even as global trade dynamics have evolved. The HOS model emphasizes the importance of factor endowments—land, labor, and capital in determining a country's production patterns. The model suggests that trade arises from differences in these endowments, with countries exporting goods that intensively use their relatively abundant factors. However, the rise of digital trade has complicated this model, as it introduces factors such as knowledge diffusion, economies of scale, and the rapid transmission of information, which affect comparative advantage beyond traditional resource endowments (Zhang, 2008). This shift suggests that even nations with similar access to technology may still engage in trade based on their differing capabilities in managing and utilizing information, which has become a critical factor in modern trade. Structural transformation is another key concept that ties closely to changes in trade patterns and economic development. Structural transformation refers to the shift of an economy from labor-intensive, low-productivity sectors to higher productivity, capital, and skill-intensive industries. Developed countries tend to be more affected by digital trade in terms of their positions in global value chains (GVCs), while developing countries, such as Ethiopia, still grapple with the complexities of digital trade's role in driving economic transformation (Wu et al., 2014). The heterogeneity of countries in terms of their development status means that the benefits of digital trade and ICT infrastructure are not equally distributed. For instance, developed countries are better positioned to integrate into digital trade networks, while developing countries face challenges in leveraging the full potential of these technologies.

The concept of "competitive advantages" refers to a country's ability to outperform others in global markets through pricing, product quality, or service. Kaleka and Morgan (2017) argue that these advantages, whether based on price, product, or service, are critical for success in the global marketplace. Price advantage arises when a country can offer goods at lower costs, product advantage is achieved when goods are superior in terms of design or quality, and service advantage is evident in aspects such as customer satisfaction and delivery speed. These competitive advantages are aligned with Porter’s (1980) differentiation and cost leadership strategies. However, trade diversification can significantly alter the competitive advantage dynamic. Countries that diversify their exports and trade portfolios are more likely to weather global market fluctuations and create new growth opportunities. Dutt et al. (2008) emphasize that wealthier nations tend to diversify their export bases over time, influenced by factors like trade costs, market access, and proximity to trading hubs. This diversification is positively linked to economic growth, as it broadens the market reach and reduces dependence on a narrow set of goods or services. For Ethiopia, export diversification has shown a statistically significant long-term positive impact on output growth (Hesse, 2009), underscoring the role of trade diversification in driving economic development. Export diversification, coupled with economic globalization, fosters growth by opening new markets and creating avenues for economic resilience. In the context of sub-Saharan Africa, research by Hodey (2015) indicates that export diversification positively impacts economic growth, further supporting the need for Ethiopia to pursue a more diverse set of exports to enhance its economic stability. Empirical evidence from countries like South Africa also corroborates this relationship, as trade openness and export diversification have been shown to positively influence growth (Mudenda, 2014). Similarly, studies on liberalization and economic growth in Ethiopia also highlight the correlation between trade liberalization and both short-term and long-term economic growth (Emagne, 2017).

AI plays an increasingly central role in modern trade by transforming traditional business practices, especially in sectors like ICT products and services. The development of AI technologies has the potential to significantly boost global trade by improving efficiencies and creating new opportunities for economic growth. For instance, AI-powered machine translation has reduced language barriers, facilitating cross-border communication and enhancing trade, especially in the digital services sector. Furthermore, AI has revolutionized logistics by optimizing warehouse management and forecasting, improving the efficiency of global supply chains. Financial services have also benefited from AI through enhanced risk assessments, personalized banking services, and compliance with regulations like anti-money laundering laws (Achar, 2019). Despite its promise, AI faces several barriers, particularly in emerging markets where ICT tariffs and infrastructural constraints limit its widespread adoption. The implementation of AI is further hindered by issues related to data accessibility and the need for advanced processing facilities (Elnahrawi, 2021). However, the potential for AI to boost trade and economic productivity is clear, especially as countries increasingly recognize the importance of integrating AI into their trade policies. AI has been shown to enhance global competitiveness, as nations that incorporate AI into their industries experience greater productivity and trade volumes (Al & Bilgiç, 2023). In addition, the development of AI has been linked to improved labor market outcomes, where countries can leverage AI to optimize labor resources and reduce inefficiencies (Jones et al., 2017).

Overall, the relationship between trade, ICT infrastructure, internet penetration, and economic growth in Ethiopia is evolving. As digital technologies like AI continue to transform the global trade landscape, Ethiopia faces both challenges and opportunities in harnessing these technologies to drive economic growth. Trade diversification, ICT infrastructure, and internet penetration remain key drivers of economic development, and the integration of AI could further enhance these factors, leading to greater economic expansion. As AI continues to advance, it holds the potential to reshape the dynamics of global trade and economic growth, offering new avenues for developing economies like Ethiopia to accelerate their integration into the global market.

Conceptual Framework

This study focused on the causal relationship between the dependent variable GDP growth rate (GDPGR) and independent variables: Trade Diversification Index (TRDI), ICT infrastructure (ICTInF, Internet penetration (IntP), and Artificial Intellegence Intergation (AII). Their causal relationship was depicted as follows:

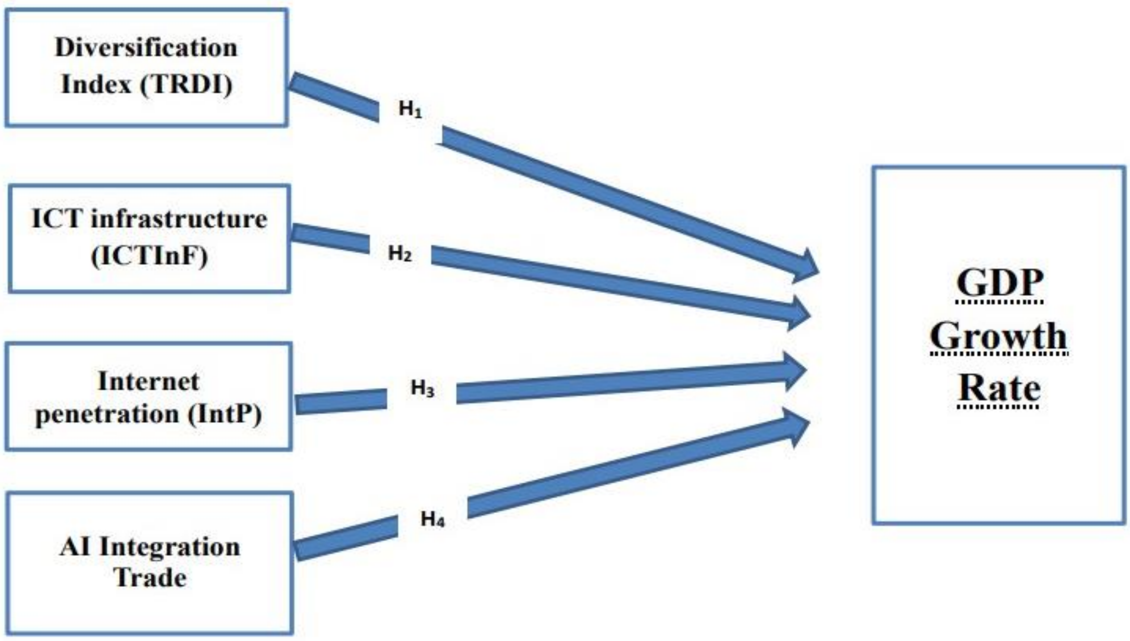

Figure1: Conceptual framework

METHODOLOGY

Ethiopia is strategically located in the Horn of Africa, 3-′15′ latitude and 33-′48′ longitude. The climate condition of Ethiopia is tropical in the southeastern and northeastern lowland region, but much cooler in the large central highland region of the country. Mean annual temperature are around 15-20°C in these high-altitude regions, whilst 25-30°C in the low land. The economic activities: agriculture, forest, fishing, textile industry, minerals and mining, manufacturing, tourism. The current population of Ethiopia is 122,543,875 based on world meter elaboration of latest united nation data.

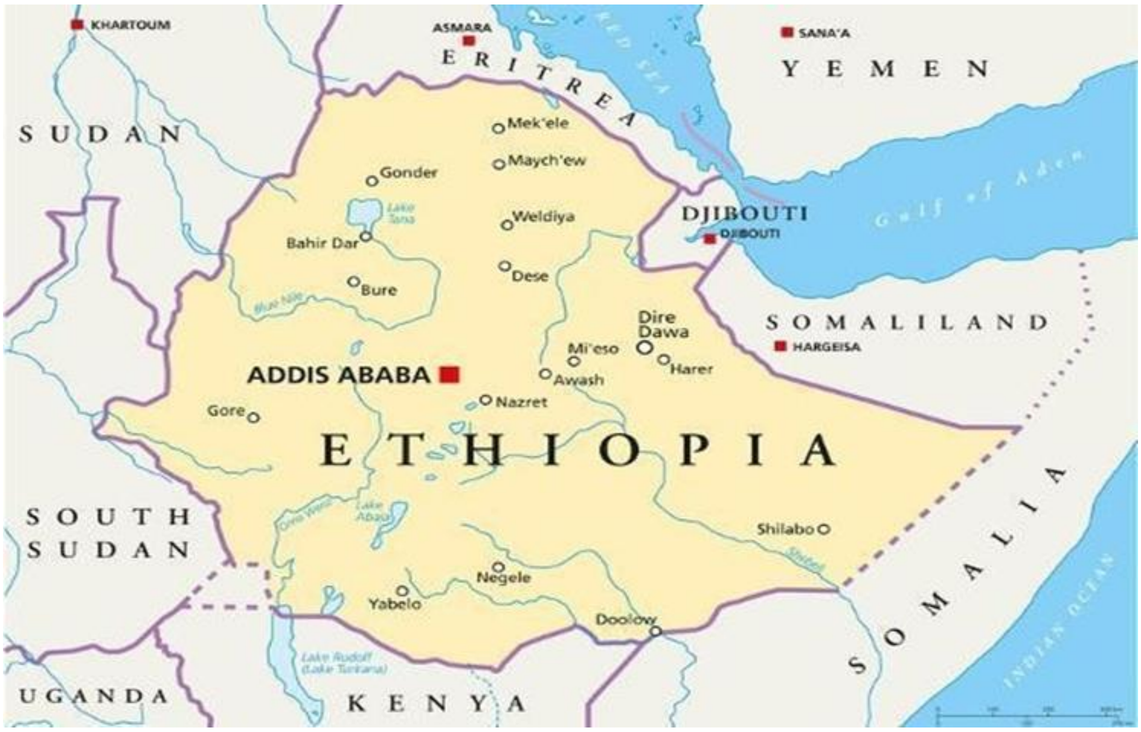

Figure 2: Location description of Ethiopia

For this study on the role of Artificial Intelligence (AI) in digital trade and its impact on economic growth in Ethiopia, an empirical quantitative research approach will be adopted. This approach is essential because it allows for the exploration of causal relationships between AI's influence on digital trade and economic growth through measurable data (Gujarati, 2003). Quantitative research uses numerical data to identify patterns and draw conclusions about economic outcomes. Given the focus on time series data, the study will analyze historical data from 1992 to 2023 to assess the influence of AI-driven digital trade on Ethiopia's economic growth. The study employs both qualitative and quantitative research designs. Qualitative design is used for the conceptual understanding of the data, while quantitative methods shape and analyze the data numerically. Time Series Analysis will be used, which is particularly effective in tracking data points recorded at evenly spaced intervals over time (Stock & Watson, 2015). This design is ideal for observing the impact of AI on digital trade, identifying trends, cycles, and long-term relationships between digital trade and economic growth in Ethiopia. Time series analysis provides valuable insights into causal relationships and forecasts future trends based on historical data, making it crucial for this research. It allows the study to identify trends in AI adoption within digital trade platforms, examine the long-term relationships between digital trade, AI integration, and economic growth, and forecast future outcomes of AI in digital trade's role in enhancing economic performance.

The data used in this study is secondary, collected from sources such as the World Bank, IMF, UNCTAD, articles, and journals. The time series data covers the period from 1992 to 2023 and investigates factors influencing GDP growth in Ethiopia's trade diversification. The analysis involves both descriptive and inferential methods using econometric models. Descriptive analysis presents the data in tables, graphs, and percentages, while the Vector Error Correction Model (VECM), using STATA software, is applied to assess the causal relationships between the variables. For this multivariate time series study, the VECM is used, where each variable is a linear function of past lags of itself and past lags of the other variables. The dependent variable is Ethiopia's GDP at constant prices, while independent variables include the Trade Diversification Index (TRDI), ICT infrastructure (ICTInF), Artificial Intelligence Integration (AII), and Internet penetration (IntP). The VECM is preferred because the variables are cointegrated at the first difference, indicating a long-term equilibrium relationship. The Johansen cointegration test is used to verify this, confirming both short-term and long-term relationships among the variables, making VECM the appropriate model for this study.

Estimation of the Econometrics Model

The Vector Error Correction Model (VECM) which was used for this study was estimated based on the major variables for this study which are stationary in the short run and long run.

General Form of VECM

$$\Delta y_t = \Pi yt - 1 + \sum_{i=1}^{p-1} \Gamma i\, \Delta y_{t-1} + ut$$

Where:

$\Delta\mathbf{y}_t$ = is the vector of differenced variables (y_t = is the original vector of variables) Γ_i = is the short-term impact matrices

p is the number of lags.

$\mathbf{u}_t$ is the vector of error terms.

Specific VECM equation for this study

There are Five variables GDP growth rate (*GDPGRt*), Trade Diversification index (TRDI*t*), ICT infrastructure (ICTInFt), Internet Penetration (IntPt) and Digital Trade Index (DGTRt), the VECM for these variables can be expressed as:

$$\Delta GDPGR_t = \gamma_{11}\,(\beta_{1.}\,ECTt - 1) + \sum_{i=1}^{p-1} \phi\, 11 i\Delta GDPGR_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 12 i\Delta TRDI_{t-1} + \sum_{i=1}^{p-1} \phi\, 13 i\Delta ICTInF_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 14 i\Delta IntP_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 15 i\Delta AII_{t-1} + \upsilon_{1t}$$

$$\Delta TRDI_t = \gamma_{21}\,(\beta_{1.}\,ECTt - 1) + \sum_{i=1}^{p-1} \phi\, 21 i\Delta GDPGR_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 22 i\Delta TRDI_{t-1} + \sum_{i=1}^{p-1} \phi\, 23 i\Delta ICTInF_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 24 i\Delta IntP_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 25 i\Delta AII_{t-1} + \upsilon_{2t}$$

$$\Delta ICTInF_t = \gamma_{31}\,(\beta_{1.}\,ECTt - 1) + \sum_{i=1}^{p-1} \phi\, 31 i\Delta GDPGR_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 32 i\Delta TRDI_{t-1} + \sum_{i=1}^{p-1} \phi\, 33 i\Delta ICTInF_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 34 i\Delta IntP_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 35 i\Delta AII_{t-1} + \upsilon_{3t}$$

$$\Delta IntP_t = \gamma_{41}\,(\beta_{1.}\,ECTt - 1) + \sum_{i=1}^{p-1} \phi\, 41 i\Delta GDPGR_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 42 i\Delta TRDI_{t-1} + \sum_{i=1}^{p-1} \phi\, 43 i\Delta ICTInF_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 44 i\Delta IntP_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 45 i\Delta AII_{t-1} + \upsilon_{4t}$$

$$\Delta AII_t = \gamma_{51}\,(\beta_{1.}\,ECTt - 1) + \sum_{i=1}^{p-1} \phi\, 51 i\Delta GDPGR_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 52 i\Delta TRDI_{t-1} + \sum_{i=1}^{p-1} \phi\, 53 i\Delta ICTInF_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 54 i\Delta IntP_t{}^{-1} + \sum_{i=1}^{p-1} \phi\, 55 i\Delta AII_{t-1} + \upsilon_{5t}$$

Where:

GDPGR = Growth Domestic product (GDP),

TRDI = Trade Diversification Index,

ICTInF = ICT infrastructure,

InP = Internet Penetration, and

AII = Artificial Intellegence Intergration

Δ: Represents the first difference of the variables.

ECT: Error Correction Term, which represents the deviation from the long-term equilibrium. This term is derived from the cointegrating relationship β_1. Which indicates ECT_{t-1}. $\gamma_{11}, \gamma_{21}\ \gamma_{31}\ \gamma_{41}\ \gamma_{51}$: Adjustment coefficients indicating how quickly variables return to equilibrium

after a change.

υ_{1t} to υ_{5t} : Error terms for each equation t = Time

Lags from 1992 to 2023.

Estimation techniques

To analyze series data for policy recommendations and conclusions, three techniques must be passed, each testing the stationarity of the time series variable. Errors in each stage must be adjusted to meet the estimation technique criteria, ensuring data validity. The following steps are necessary to pass these stages and progress to the next stage.

Stationarity test: Unit root test

Before conducting an economic study, it is crucial to ensure the data is stationary, meaning its mean, variance, and co-variances remain constant over time. Non-stationary data may lead to spurious results. In the time series econometrics, the random walk time series has a unit root, and the Augmented Dickey Fuller (ADF) test was used to test unit roots. Non-stationary data can result in spurious results. Therefore, it is essential to check data for stationaryity. Therefore, the unit root tests using Augmented Dickey-Fuller tests were conducted and all variables are integrated of order zero I(0) and order one I(1).

Testing for Existance of Longrun Relationship

To test for the existence of a long-run relationship among variables, Johansen co-integration test and the Engle-Granger two-step method were applied and the result shows that there is Longrun and short run relationship among the variables in this study. Therefore, using VECM is more appropriate for this study.

Post estimation (Diagnostic) tests

For VECM model which is nonstationary at level and stationary at integrated of order one I (1), the most prefered diagnostic tests are: Lagrange-multiplier test to test for serial correlation among lags of variables, Jarque-Bera test for Normality test and other tests like Skewness test and Kurtosis tests were conducted.

Data Analysis and interpretation

This section revealed that the trends of dependent variable (GDP growth) followed by various independent variables incorporated in the model. The aim of this trend analysis is to serve as a basis for the basic analysis of the econometric results.

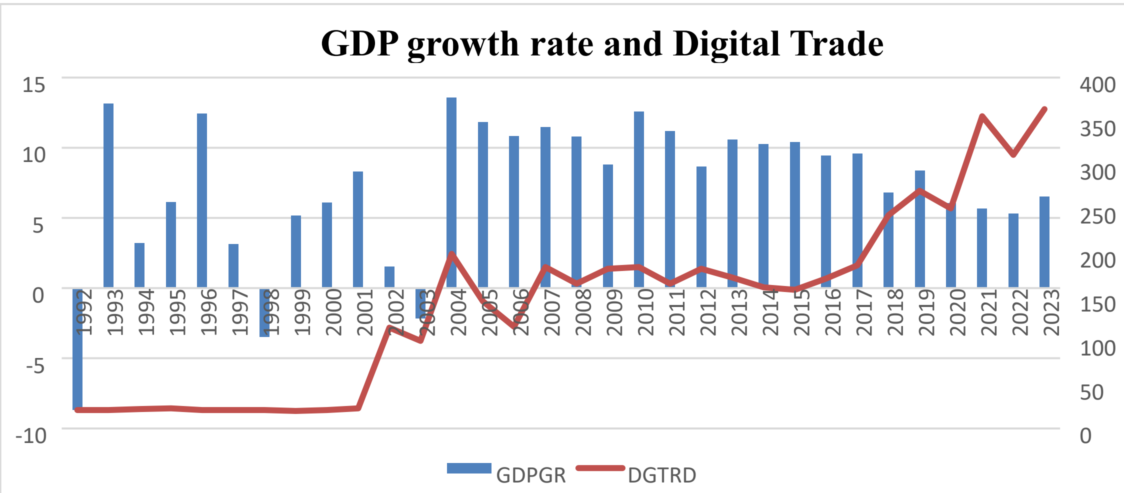

Figure 3. GDP growth rate and Trade diversification Index.

Observed Trends between GDP and Digital Trade: Based on Figure 3 above shows that: GDP Increases as Digital Trading system become more diversified: from 1992 to the year 2004 there were a dynamic increase in Digital trade usage in Ethiopia. This Digital Trade application process needs high costs and adoptations. Therefore, in these initial years there were minimum results of Digital Trade that led to small change on GDP growth rate. Then after the trend shows that as trade diversification increases that leads to

Digital trade increased then, GDP growth rate also increase and if it decreases, they decrease together I'e to increase economic performance and growth in the economy diversifying trade specially export diversification is very important.
The trend relationship between GDP and ICT infrastructural development were discussed as follows using the world bank development index data from 1992 to 2023.

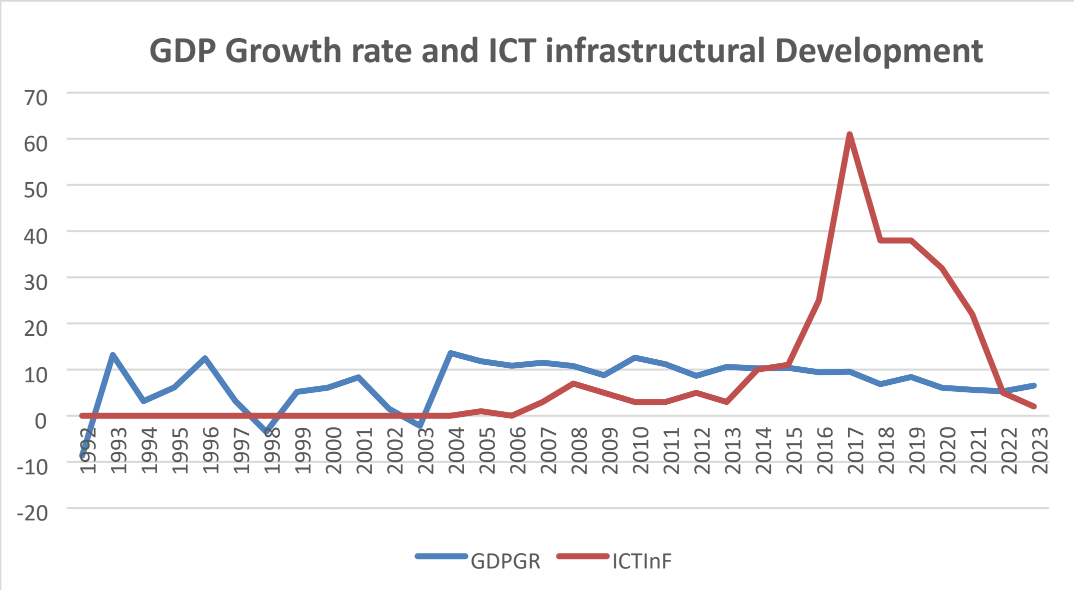

Figure 4. GDP growth and ICT infrastructural Development (1992 -2023).

The study reveals a positive correlation between Ethiopia's GDP growth and ICT infrastructural development over a 32-year period. This positive relationship is attributed to factors such as globalization and high demand for ICT as the economy develops, indicating a positive correlation between GDP growth and ICT infrastructure. The growth of ICT infrastructure in the Philippines was slow, with growth rates less than GDP growth up to 2014. From 2014 to 2018, there was a high increase in ICT infrastructure development, with expansions occurring. However, after 2019, ICT infrastructure development decreased due to the COVID-19 pandemic and civil war, affecting the GDP growth rate.
The below figure 5 shows a positive trend relationship between GDP growth and Internet penetration. As GDP growth rate had been increasing from year to year, individuals in the country using internet had been icreasing. The rate increament in GDP was higher thatn the rate of increament in Internet penetration upto the year 2014. But after the year 2014, it has been highly increasing which indicates the people adopts using internet and the number of individuals using internet for their businesses as well as throughout their life is increasing.

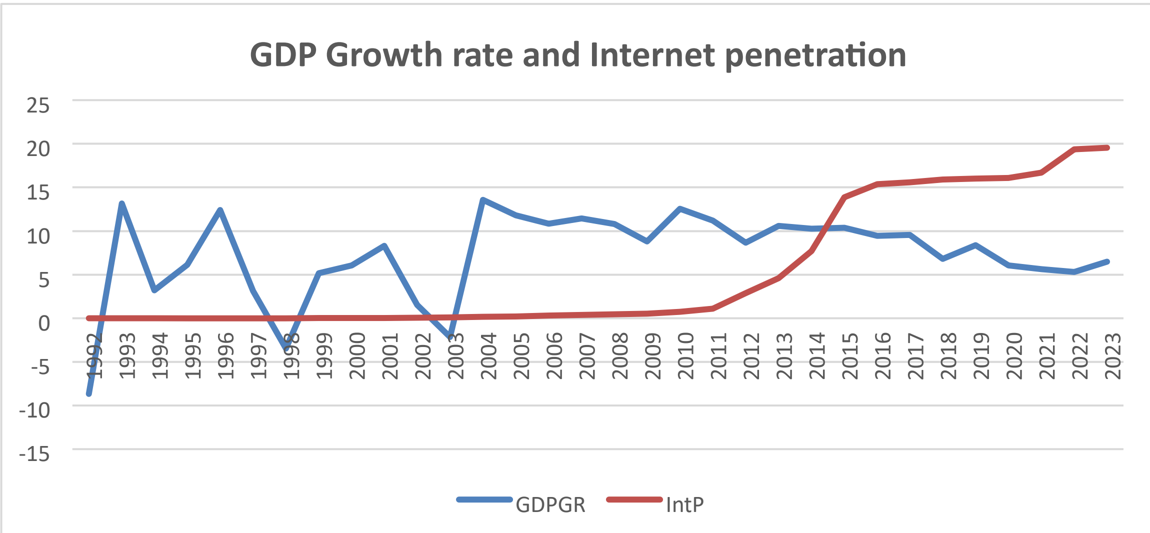

Figure 5. Internet penetration and GDP growth rate (1992 -2023).

The relationship between GDP growth and Trade Diversification Index is positive, as diversified trade from agriculture to manufacturing increases the economy's export capacity, leading to increased GDP. This can be achieved by diversifying from single export items to multiple agricultural products, manufacturing, and service exports, and can be achieved using Export Import

Substitution (EXIM) policy. Therefore, the increase in GDP from year to year is likely due to improvement in Trade diversification in export dynamics and sectoral diversification in Ethiopian economy in the last two and half decades as shown by the following figure.

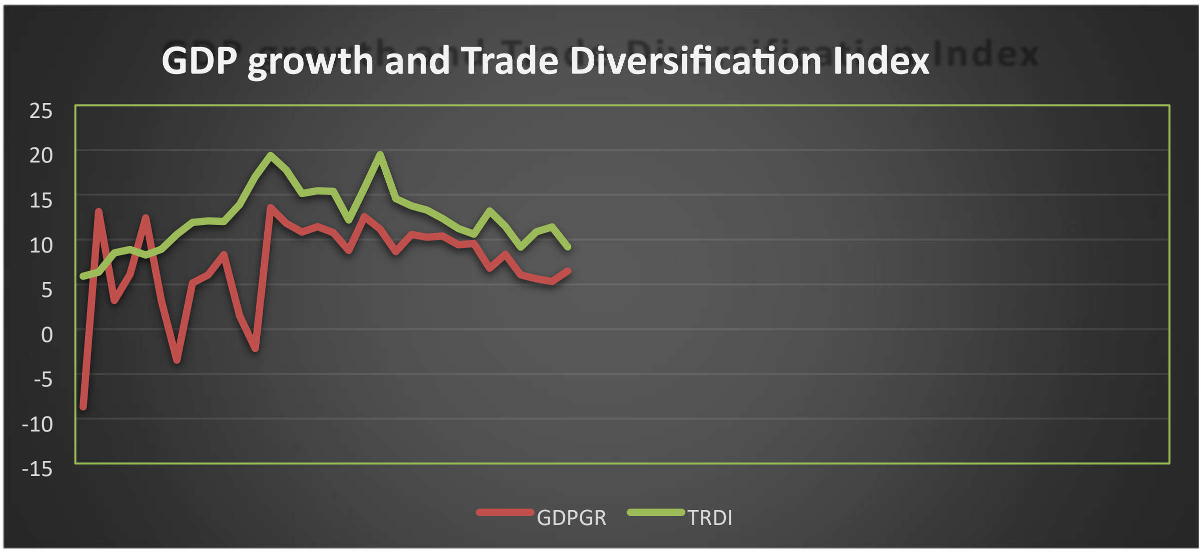

Figure 6: Trend relationship between GDP growth and Trade Diversification (1992 -2023).

Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
years	32	2007.5	9.381	1992	2023
GDPGR	32	7.293	5.062	-8.672	13.573
TRDI	32	12.382	3.434	5.912	19.491
ICTInF	33	8.364	14.603	0	61
IntP	32	5.243	7.376	0	19.543
DGTRD	32	143.625	102.639	20	364
GDPGR d1	31	.489	6.287	-9.953	21.815
TRDI d1	31	.105	2.047	-4.9	3.74
ICTInF d1	31	.065	9.216	-23	36
IntP d1	31	.63	1.311	0	6.155
DGTR d1	31	11.065	38.779	-54	105

As shown by the above table for the time series data of 32 years, the most dispersed variable with high mean is Digital trade that accounts 143.625 and less dispersed variable accompanied by low mean is Internet penetration which is 5.243, and the most dispersed variable with high standard deviation is also Digital trade and the lowest despersed variable with low standard deviation is Trade Diversification Index respectively as shown by the standard deviation and mean in the above table.

RESULTS AND FINDINGS

To improve policy recommendations, series data must pass three estimation techniques: stationarity, normality, and diagonal tests. These tests test the stationaryity of the time series variables. Any errors in each stage must be adjusted to meet the criteria of the estimation techniques, ensuring progress into the next stage. The study utilized time series data from 19922023, incorporating one dependent and four independent variables, and employed time series analysis techniques to collect data on one or more variables over a specific period. In this section the results of the test for Normality, stationarity tests, Diagonastic tests and VECM regression result both in short run and long run are presented.

A stationary time series is one whose statistical properties such as mean, variance, co- variance and autocorrelation are all constant over time. The augmented dickey fuller (ADF) unit root test is conducted to identify whether the study data is stationary or nonstationary.

Table 2: Stationarity test: ADF unit root test

variable	t-statistic z(t)	1% Critical Value	5% Critical Value	10% Critical Value	p-value for z(t)	Decision
GDPGR	-5.900	-4.325	-3.576	-3.226	0.000	I (0)
TRDI	-2.558	-2.473	-1.703	-1.314	0.0161	I (0)
ICTInF	-3.351	-2.479	-1.706	-1.315	0.0012	I (1)
IntP	-2.645	-2.479	-1.706	-1.315	0.0068	I (1)
DGTR	-4.223	-2.479	-1.706	-1.315	0.0001	I (1)

The above table shows that some variables are stationary at First difference and some of the are stationary at level for which its P-value is significant at all levels. This implies that a regression based on the above variables can explain the relationship among the variables; and there is no spurious relationship in the study data. So, since it stationary at first difference and level it shows there is co-integration both in shortrun and longrun forthis reason wennot use OLS, and we can use other methods Like VECM and VAR Model. Therefore, for this study to show the short run and long run relationship between variables, the VECM model (vector Error Correlation Model) was used for the analysis of these data.

4.3 Lag selection

Table 3: Lag selection

```
varsoc GDPGR TRDI ICTInF IntP DGTRD, maxlag(3)

Selection-order criteria
Sample:  1995 - 2023                      Number of obs     =        29
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-512.058				2.1e+09	35.6592	35.733	35.8949
1	-417.731	188.65	25	0.000	1.8e+07	30.878	31.321	32.2924
2	-393.607	48.248	25	0.003	2.3e+07	30.9384	31.7505	33.5315
3	-331.903	123.41*	25	0.000	3.0e+06*	28.4071*	29.5884*	32.1789*

```
Endogenous:  GDPGR TRDI ICTInF IntP DGTRD
 Exogenous:  _cons
```

Based on the above Lag selection- order criteria, lag 3 order (1) is the best posibility. Because-28.4071 is the lowest coefficient at AIC.

The Johansen test result for co-integration shows that there is at least one co-integrated equation at rank (2). The result shows that there is integration equation at rank (2). The egen value result shows that it is significant and cointegrated. As shown by the following table, the trace statistics value is higher than the 5% critical value for the first three lagas of Eigen value. Therefore, we reject null hypothesis and conclude that there is at least one co-integrating equation.

Table 4: Johansen Cointegration test

```
. vecrank GDPGR TRDI ICTInF IntP DGTRD, trend(constant) lags(3) max

                    Johansen tests for cointegration
Trend: constant                                   Number of obs =      29
Sample:  1995 - 2023                                       Lags =       3
```

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	55	-395.0388	.	126.2724	68.52
1	64	-356.46936	0.93005	49.1336	47.21
2	71	-340.80311	0.66055	17.8011*	29.68
3	76	-335.8478	0.28947	7.8904	15.41
4	79	-331.97066	0.23462	0.1362	3.76
5	80	-331.90258	0.00468		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	55	-395.0388	.	77.1389	33.46
1	64	-356.46936	0.93005	31.3325	27.07
2	71	-340.80311	0.66055	9.9106	20.97
3	76	-335.8478	0.28947	7.7543	14.07
4	79	-331.97066	0.23462	0.1362	3.76
5	80	-331.90258	0.00468		

Table 5: Summary of short Run Vector Error correlation Model Result

GDPGR	Coef.	Std. Err.	Z	P>z	[95% Conf. Interval]	
TRDI	.7555543	.5945393	1.27	0.204	-.4097212	1.92083
ICTInF	.3521632	.218125	1.61	0.106	-.075354	.7796804
IntP	-2.304595	.6606387	-3.49	0.000	-3.599424	-1.009767
DGTR	-.0695432	.0290371	-2.39	0.017	-.1264549	-.0126315

The above short run result shows the dynamic short run relationship between dependent variable and independent variables. In short run if there is one percent change in Internet Penetration (IntP) there is 230% change in GDP, if there is 1% change in Digital Trade (DGTR) in Ethiopian economy, there will be 6.95% change in GDP positively. Whereas, in the short run Trade Diversification and ICT infrastructure variables are not significant. Ingeneral, this short run result shows that there is significant and positive relationship between dependent variable GDP with Internet penetration (IntP) and Digital Trade (DGTR). And there is a significant and negative relationship between dependent variable GDP and independent variables Trade Diversification (TRDI) and ICT Infrastructure (ICTInF) are insignificant in the short run as shown by this data.

The below long run result shows that the Cointegrating equations which indicate betas are exactly identified and the long run Vector Error Correlation result were displayed using Johansen normalization restriction tables as follows.

Table 6: Long Run Vector Error correlation Result

Variables	Coef.	Std. Err.	z	P>z	[95%]	Conf.
D_GDPGR_d1 | _ce1 L1	-1.888282	.4346217	-4.34	0.000	-2.740125	-1.036439
GDPGR_d1	.6087749	.2993607	2.03	0.042	.0220387	1.195511
TRDI_d1	.1133958	.3368612	0.34	0.736	-.5468399	.7736315
ICTInF_d1	-.1639867	.0812791	-2.02	0.044	-.3232907	-.0046826
IntP_d1	.6122201	.7517576	0.81	0.415	-.8611978	2.085638
DGTR_d1	-.090959	.0268023	-3.39	0.001	-.1434906	-.0384274
D_TRDI_d1 _ce1 | L1.	-.4208624	.2010678	-2.09	0.036	-.8149481	-.0267767
DPGR_d1	.1776463	.1384924	1.28	0.200	-.0937938	.4490864
TRDI_d1	-.4104962	.1558411	-2.63	0.008	-.7159392	-.1050532
ICTInF_d1	.037833	.0376019	1.01	0.314	-.0358653	.1115314
IntP_d1	.3384721	.3477835	0.97	0.330	-.3431711	1.020115
DGTR_d1	-.0123408	.0123995	-1.00	0.320	-.0366433	.0119618
D_ICTInF_d1 _ce1 L1	-.6220938	.0627177	-9.92	0.000	-.7450182	-.4991694
D_IntP_d1 _ce1 L1	-.0028597	.152154	-0.02	0.985	-.3010759	.2953566
D_DGTR_d1 _ce1 L1.	-1.177834	.2493227	-4.72	0.000	-1.666498	-.6891705

The long-term Vector error correlation (VECM) results indicate that GDP growth rate, Trade Diversification Index, ICT infrastructure, and Digital Trade are significant at a 5% level of significance, with a P-value less than 5% (0.005). All variables are significant except Internet penetration, indicating that all independent variables can explain dependent variables individually. This aligns with the rule that negative coefficients of integrated variables should be interpreted as positive impact and statistically significant in the long run. The study indicates that a 1% increase in Trade Diversification policy effectiveness can boost Ethiopia's GDP growth rate by 42.08624%. Additionally, a 1% improvement in ICT infrastructure can increase the Ethiopian economy's GDP growth rate by 62.211%. Furthermore, a 1% increase in Digital Trade Diversification activities can increase the GDP growth rate by 117.7834 percent. Therefore, these long-run relationships result show that GDP growth is very sensitive to change if there is a little change in driving Macro Economic variables like Trade Diversification (TRD), ICT infrastructure development (ICTInF), and Digital Trade usage implimentation (DGTR) which are highly influence the growth and fall of the economy's GDP.

The Langrange-multiplier test result shows that all P-value is greater than 0.05 and significant which indicates that there is no autocorrelation at order, and we can accept null hyphothesis. Lagrange-multiplier test

Table7, Langrange-multiplier test for autocorrelation.

Lag	chi2	df	Prob>Chi^2
1	20.6932	25	0.70959
2	28.2083	25	0.29835
3	35.9170	25	0.07287

H0: no autocorrelation at lag order

The Jarque-Bera (JB) test is used to test the normality of the residuals in the VECM. Ensuring that the residuals are normally distributed is important because many inference procedures (such as hypothesis testing) in time series econometrics rely on the assumption of normality. Which means if the residuals are not normally distributed, it could indicate potential issues with model specification, such as omitted variables, incorrect lag length, or nonlinearity. If the p-value is high (typically > 0.05), you fail to reject the null hypothesis, suggesting that the residuals are normally distributed. Therefore, in our case since P-Value is greater than 0.05 (5%) level of significance accept null hypothesis and conclude that the residuals are normally distributed. See the following table:

Table 8: Jarque- bera test result for nornality

Jarque-Bera test

Equation	Skewness	chi2	df	Prob > chi2
D_GDPGR_dl	.78638	2.886	1	0.08936
D_TRDI_dl	.16788	0.132	1	0.71686
D_ICTInF_dl	-1.135	6.012	1	0.01421
D_IntP_dl	-.65499	2.002	1	0.15708
D_DGTR_dl	-.06278	0.018	1	0.89213
ALL		11.049	5	0.05041

The Eigenvalue test is part of the Johansen cointegration test procedure. It is used to determine the number of cointegrating relationships among the variables in the VECM.

Table 9: Eigen value result

Eigenvalue stability condition

Eigenvalue	Modulus
1	1
1	1
1	1
1	1
-.7871599 + .4400699i	.901822
-.7871599 - .4400699i	.901822
-.2574523 + .8288416i	.867906
-.2574523 - .8288416i	.867906
-.507509 + .6690403i	.83975
-.507509 - .6690403i	.83975
-.04342187 + .8009152i	.802091
-.04342187 - .8009152i	.802091
.2986821 + .5755249i	.648413
.2986821 - .5755249i	.648413
-.1472437	.147244

The VECM specification imposes 4 unit moduli.

If the maximum eigenvalue and trace statistics are greater than the critical values, you reject the null hypothesis of no cointegration (or fewer cointegrating vectors) and conclude that there is at least one cointegrating relationship. The number of cointegrating relationships determined here (rank) should be used in specifying the VECM. In our case, since all values are greater than 0.05 (5%) level of significance, we can conclude that there is at least one cointegrating relationship. It is indicated by the following table.

CONCLUSION AND RECOMMENDATIONS

This study investigates the role of digital trade in the economic development of the Ethiopian economy, with GDP growth rate as the dependent variable and digital trade volume, internet penetration, ICT infrastructure, and trade diversification index as independent variables. The findings provide insightful implications for policymakers and stakeholders in Ethiopia's digital and economic sectors. The empirical analysis, conducted using time series data, reveals that digital trade significantly contributes to Ethiopia's economic development, particularly in the long run. All independent variables digital trade volume, internet penetration, ICT infrastructure, and trade diversification index show a positive and significant relationship with GDP growth both in the short run and long run. This emphasizes the transformative potential of digital trade in boosting productivity, improving market access, and fostering economic diversification over time. In the short run, however, the results indicate that only digital trade volume and internet penetration significantly impact GDP growth. This suggests that these variables have immediate effects, likely due to their direct role in reducing transaction costs, enhancing communication, and expanding market opportunities. In contrast, ICT infrastructure and trade diversification index are not significant in the short run, which could reflect the time lag required for infrastructure investments and diversification strategies to yield measurable economic benefits. whereas all of them have significant impacts on GDP in the long run. This study focuses on the key macro economic variables that influece the GDP rate through trade Diversification, to diversify trade in different dynamics using E-commenrce for digital trade, ICT infrastructural development and Internet broadband exparsion which very importatnt variable to diversify trade. This makes this study unique from other emipirical studies in this area.

Recommendations

The Ethiopian economic policy makers should continue to recommend and encourage stablishement and expassion of these key factors to diversify trade as well as to increase economic growth through:

- Accelerating Internet Penetration: this needs Immediate efforts to increase internet accessibility and affordability that can deliver quick gains in economic growth.
- Promoting Digital Trade: Incentivizing the adoption of digital platforms for trade and adopting E-commerce should be a priority for short- and long-run economic benefits.
- Long-run Investments in ICT Infrastructure: Although not significant in the short run, investments in ICT infrastructure are crucial for sustaining economic development in the long run because it can play a key role to bring economic development of the country.
- Enhancing Trade Diversification: Policymakers should focus on strategies that expand Ethiopia's export base to fully realize the economic potential of digital trade. This can also need to focus on diversifying export from agriculture to manufacturing Item.

In General, digital trade represents a critical pathway for Ethiopia’s economic transformation. While its short-run impacts are primarily driven by connectivity and digital trade volume, the longterm benefits underscore the need for a comprehensive digital strategy that integrates infrastructural development, trade diversification, and digital trade platform inclusion.

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