

The investigation of the interrelationship between digitalization and gross domestic product in Azerbaijan

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Abstract: Digitalization is widely recognized as a key driver of economic growth and sustainable development. This study examines the relationship between digitalization and economic growth in Azerbaijan from the perspective of the economic dimension of digitalization. Instead of using infrastructure-based indicators, digitalization is measured by ICT value added and ICT product imports, as these variables directly reflect the economic contribution of the ICT sector and the diffusion of digital technologies in Azerbaijan. Gross Domestic Product (GDP) is employed as the indicator of economic growth. Given the possibility of reverse causality, alternative model specifications are estimated in which GDP and ICT-related variables are treated alternately as dependent and explanatory variables. The empirical analysis applies OLS, ARDL Bounds Testing (ARDLBT), FMOLS, DOLS, CCR, and the Vector Error Correction (VEC) model to estimate both the short-run and long-run relationships. The results indicate that ICT value added and ICT product imports individually exert a positive and generally statistically significant effect on economic growth. However, when both ICT indicators are included simultaneously, the effect of ICT product imports becomes statistically insignificant and, in some specifications, negative. The findings suggest that the contribution of digitalization to economic growth in Azerbaijan remains constrained by the structural characteristics of the economy, particularly the dominant role of the hydrocarbon sector.

Keywords: Digitalization; Information and Communication Technologies (ICT); ICT Value Added; ICT Product Imports; Economic Growth; Gross Domestic Product (GDP); ARDL Bounds Testing.

JEL Classification: C22, E01, O11, O47, O39

1 Introduction

The “digital revolution” unfolding in the modern world has significantly reduced economic, social, and geographical constraints, transforming digitalization into a decisive factor in accelerating innovation-driven economic growth, facilitating the transition to a sustainable and inclusive development model, and improving overall governance systems. The experience of developed countries clearly demonstrates that the widespread implementation of innovative digital strategies across all sectors of society and the economy has enabled them to achieve dynamic economic growth.

According to the Digitalisierungsindex, 2024 report, the development of digital infrastructure has a positive impact on aggregate demand in the short term and contributes to the acceleration of economic growth. Technological progress, in turn, reduces production costs, lowers prices, and stimulates demand expansion, thereby fostering an increase in real Gross Domestic Product (GDP). The extensive use of digital technologies affects the growth dynamics of the national economy through several key transmission channels. These include technological progress stimulated by digitalization, the transition toward the sharing economy, structural changes in employment patterns, the effective utilization of time savings generated by

technological advancements, increased investment demand, and the broader contribution of technological progress to economic growth [26].

The digital economy serves as a powerful instrument for reducing various types of costs-time, financial, and material-thereby accelerating processes across all stages of economic reproduction. This leads to cost reductions, increases in labor productivity, and improvements in the overall efficiency of economic systems. Furthermore, information resources create opportunities for the implementation of innovative methods and tools, attract businesses to emerging sectors of the economy, lower barriers to market entry, and positively influence the country's socio-economic development.

The *Global Connectivity Index 2025* report prepared by Huawei (2025) indicates that every US dollar invested in ICT infrastructure generates approximately USD 3–5 in additional GDP growth over the long term. It should also be emphasized that ICT development not only accelerates economic growth but also enhances labor productivity and contributes to job creation. According to expert estimates, by 2030, approximately 30% of jobs in developed and rapidly developing countries will be automated, while 77% of the workforce will require new skill sets [27].

The comprehensive digital transformation of all sectors, spheres, and levels of the national economy enables the identification and objective assessment of long-term economic growth potential, as well as the determination of optimal solutions to strategic development goals. In this process, economic efficiency and social inclusiveness are considered fundamental criteria.

In Azerbaijan, the practical transition to a digital economy effectively began in 2003 with the adoption of the “National Strategy on Information and Communication Technologies for the Development of the Republic of Azerbaijan.” Subsequently, the 2016 “Strategic Roadmap for the Development of Telecommunications and Information Technologies in the Republic of Azerbaijan” emphasized that ICT has the potential to transform various aspects of business and trade operations. By leveraging ICT for regulatory optimization, service support, and efficiency enhancement, the government could generate additional economic benefits. In accordance with this document, a corresponding “digital transition plan” was developed [2].

In recent years, the digital transformation of the economy and society has become one of the key priorities of the Republic of Azerbaijan. The widespread digitalization of public services has created a strong foundation for effective digital transformation. The “Digital Transformation Strategy of the Republic of Azerbaijan for 2021–2030” outlines three main objectives: transparency and awareness, governance and coordination, and the support of digital applications. For each objective, priority directions for phased implementation have been clearly defined.

Considering the growing importance of artificial intelligence (AI) for sustainable and efficient national economic development and environmental balance, the

“Artificial Intelligence Strategy for 2025–2028” was approved in 2025. The primary objective of this strategy is to accelerate the development of the AI sector, create favorable conditions for the widespread application of AI technologies across all areas of public and economic life, and strengthen digital economic development as a key pillar of national progress. The strategy identifies priority areas such as large-scale AI implementation, the establishment of data centers, and the future expansion of digitalization sectors [3].

The Government of the Republic of Azerbaijan adopted a state-level decree establishing the Digital Development Council of the Republic of Azerbaijan to identify priority areas in digitalization, e-government, artificial intelligence, and innovation; strengthen national technological capacity; reinforce digital sovereignty; accelerate the transition to an innovation-driven economic model; and ensure the unified and coordinated implementation of state policy in these domains [4]

At the same time, digitalization leads to the disappearance of many traditional roles in the labor market, resulting in workforce displacement. Although businesses may reduce costs through AI adoption—thereby achieving economic efficiency—this process can increase unemployment and social tension, as workers face the necessity of retraining or acquiring new professions. Furthermore, the adaptation of the labor market to rapidly changing economic conditions, particularly in the context of digital transformation, often lags behind the pace of technological advancement, thereby intensifying social challenges.

Justification for the Selection of Digitalization Indicators

Digitalization is widely recognized as a multidimensional concept encompassing digital infrastructure, digital connectivity, digital skills, the adoption and use of digital technologies, digital public services, and the economic outcomes generated by digital transformation. Accordingly, previous studies have employed a broad range of proxy variables, including Internet users, fixed broadband subscriptions, mobile cellular subscriptions, the Digital Adoption Index (DAI), the Digital Economy and Society Index (DESI), the ICT Development Index (IDI), and the E-Government Development Index (EGDI).

The objective of the present study, however, is not to measure the overall level of digitalization, but rather to evaluate the direct macroeconomic contribution of the digital sector to economic growth in Azerbaijan. For this reason, the analysis focuses on two variables that directly reflect the economic dimension of digitalization.

The first indicator, value added generated in the ICT sector, measures the productive capacity of the digital economy by capturing the value created through information and communication technology activities. Unlike infrastructure-based indicators such as Internet penetration or broadband subscriptions, ICT value added reflects

the actual economic output generated by digital technologies and therefore provides a direct measure of the sector's contribution to Gross Domestic Product.

The second indicator, imports of ICT products, was selected because Azerbaijan remains largely dependent on imported digital equipment, hardware, communication technologies, and other ICT-related products. As domestic production of ICT goods is relatively limited, imports constitute the primary channel through which digital technologies are introduced into the national economy. Consequently, ICT imports represent an important indicator of digital capital accumulation and technological diffusion, particularly in developing and resource-dependent economies.

Moreover, the choice of these variables is consistent with the structural characteristics of the Azerbaijani economy. Unlike many developed economies, where digital infrastructure has already reached a mature stage and indicators such as Internet penetration exhibit relatively limited variation over time, Azerbaijan continues to rely substantially on imported digital technologies while simultaneously expanding domestic ICT production and value creation. Therefore, ICT value added and ICT imports provide more informative measures for assessing the economic effects of digitalization than purely infrastructure-based indicators.

It should also be acknowledged that these variables do not capture every dimension of digitalization. Instead, they represent the economic and production-oriented dimensions of digital transformation. Consequently, the findings of this study should be interpreted within this specific conceptual framework rather than as a comprehensive assessment of digitalization in its broadest sense. Future research may extend the analysis by incorporating additional indicators of digital infrastructure, digital adoption, digital skills, and e-government development to construct a more comprehensive multidimensional measure of digitalization.

2 Literature review

The interrelationship between digitalization and economic growth has become one of the most relevant issues in contemporary economic research.

In the modern era, digitalization is not merely characterized by the emergence of new technologies; rather, it constitutes a structural transformation that significantly influences economic performance and long-term growth dynamics. Raeskyesa and Lukas (2019) examined the relationship between digitalization and economic growth in eight middle-income ASEAN countries over the period 1999–2014 using panel regression analysis. Their findings indicate that information and communication technologies (ICT), alongside physical and human capital, exert a statistically significant positive effect on economic growth. The authors recommend

that countries invest in human capital development to maximize the benefits derived from ICT utilization [53].

Solomon and Van Klyton (2020) investigated the impact of digital technologies on economic growth in 39 African countries between 2012 and 2016. Their study differs from others by separately analyzing ICT usage by individuals, firms, and governments. Employing a system Generalized Method of Moments (GMM) estimation based on the Networked Readiness Index, the authors concluded that individual ICT usage has a positive and significant impact on economic growth [54].

Some theorists argue that the development and diffusion of digital and other technologies may generate only modest productivity gains, and that the net employment effect of digitalization could be negative. However, the extent to which innovation-driven growth in new products and services compensates for potential labor displacement remains uncertain [6].

Aleksandrova A et al. (2022) assessed the impact of digitalization on economic growth in Russia using indicators such as the Digital Adoption Index, the Index of Digital Life, GDP per capita, the Resilience Index, and the Global Competitiveness Index. Their empirical findings suggest that insufficient digital readiness of the population and macroeconomic constraints limit the ability of digital technologies to significantly accelerate economic growth [5].

Hina Asma et. al. (2024) analyzed the relationship between digitalization and economic growth across 87 developing countries over the period 2000–2024 using a panel Autoregressive Distributed Lag (ARDL) model. The results demonstrate that the Digital Index (DI), Gross Fixed Capital Formation (GFCF), Labor Force Participation Rate (LFPR), and Broad Money (M2) positively affect economic growth. The study recommends increasing investment in digital infrastructure and technology adoption to stimulate economic expansion [7].

Several studies confirm the positive contribution of digital development to economic growth. Török, L (2024) examined the impact of digital evolution on economic growth in European Union (EU) member states between 2015 and 2022 using indicators from the Digital Economy and Society Index (I-DESI). Pearson and Spearman correlation analyses confirmed a positive relationship between digital development and GDP per capita. Countries with higher levels of digitalization tend to demonstrate higher income levels and stronger growth dynamics, particularly among more advanced EU economies [58].

Magoutas, A. et. al, (2024) analyzed the dynamic relationship between ICT development and economic growth across all 27 EU member states using data from DESI 2022, EUROSTAT, and OECD reports. Through structural equation modeling, they identified a positive correlation between ICT development and GDP. The study emphasizes the accelerating role of artificial intelligence adoption in the business sector as a key driver of technological progress and economic growth [41].

Zhang et al. (2024) examined the impact of digital industrialization on economic growth in China during 2011–2019 using double fixed-effects and spatial Durbin models. Their results indicate a positive relationship, suggesting that digital industrialization enhances the efficiency of economic growth [59].

Jangid H.et. al, (2024) investigated the effects of digitalization on economic growth in G20 countries over the period 2010–2020 using a panel ARDL approach. Their findings reveal a positive long-run relationship but a negative short-run correlation between digitalization and economic growth [30].

The contribution of digitalization to Gross Domestic Product was examined within the framework of the European Union’s Digital Agenda and the Hungarian National Info communication Strategy, based on a sample of 1,045 small and medium-sized enterprises operating in Hungary during the period 2010–2018. The level of digitalization was measured using the Digital Economy and Society Index (DESI), while the contribution to GDP was assessed through indicators such as the number of employees, wage expenditures, and turnover.

By employing a least squares structural equation modeling approach, the study found that the current financial position of an enterprise is a key determinant of its contribution to GDP. However, digitalization-particularly the implementation of software systems-also plays a significant role in enhancing firm performance. Therefore, the continuation of digitalization efforts is considered essential for achieving sustainable economic growth [57].

The impact of digital technologies on economic growth and social development has also been examined in the context of developing countries. Key dimensions of digitalization, including e-commerce, digital payments, and the application of technology in social services, have been analyzed. Alongside the positive effects of this process, issues such as the digital divide, inclusive development, information security, and data privacy must also be taken into consideration during the implementation of digital technologies. Overall, the adoption of digital technologies is expected to stimulate economic and social development in developing countries, thereby contributing to sustained future growth [17].

Ghita Regasse and Zineb Karfa (2025) investigated the impact of digitalization on Gross Domestic Product in seven European countries-Germany, France, Italy, Sweden, Austria, the Czech Republic, and Hungary-over the period 2017-2022. Using the Panel Data Method, their findings indicate that the Digital Economy and Society Index (DESI) and R&D expenditures exert a positive effect on economic indicators [23].

Digital technologies influence economic growth by affecting multiple sectors of the national economy. Therefore, regardless of their level of development, European Union member states consider digitalization a driving force of economic prosperity. The application of digital tools to economic growth in the EU-27 countries was examined for the period 2017–2021. Employing Principal Component Analysis

(PCA) and the Ordinary Least Squares (OLS) model, the study found that prior to the pandemic, the level of digitalization was below average, reflecting limited technological progress. Countries with higher levels of digitalization exhibited stronger economic development. The results suggest that achieving long-term economic growth requires restructuring national digitalization strategies and accelerating the implementation of digital technologies [39].

A comparative analysis of the impact of digitalization on economic growth in the European Union and BRICS-T countries was conducted by Kasap A. (2025). Using Panel Data Analysis, the study examined EU countries for the period 2001–2022 and BRICS-T countries for 2003–2021. The findings indicate that in EU countries, internet usage, broadband access, and gross capital formation positively affect economic growth. In BRICS-T countries, the main drivers of economic growth were identified as mobile cellular subscriptions, internet usage, and gross capital formation. The study emphasizes the importance of digital infrastructure for economic development and recommends optimizing digitalization processes in both developed and developing economies [36].

From a globalization perspective, digitalization can be regarded as a key driver of technological advancement. This development exerts a strong impact on economic efficiency and Gross Domestic Product. In economies that are heavily dependent on oil revenues and classified as developing, such analyses require deeper investigation. Neffati, M. (2025) examined the impact of digitalization on economic growth in Saudi Arabia over the period 1990–2022 [43]. By applying Ordinary Least Squares (OLS), Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegration Regression (CCR) models, the study concluded that digitalization makes a significant contribution to economic growth in both the short and long run.

The influence of digital technologies on economic growth has been widely analyzed across countries worldwide. Similar analyses are also being conducted for the economy of the Republic of Azerbaijan. Notably, in 2025, the President of the Republic emphasized the relevance of assessing the impact of digitalization on economic growth and issued a decree concerning the implementation of the relevant Strategy. The Strategy focuses on accelerating digital transformation across economic sectors to achieve economic growth and ensuring the implementation of comprehensive measures in this direction [3].

3 Statistical database, methods and methodology

To examine the relationship between the digital economy and economic growth, Gross Domestic Product (GDP), value added generated in the ICT sector, and ICT product imports were selected as the main variables. Initially, GDP was considered

the dependent variable, while value added in the ICT sector and ICT product imports were treated as independent variables.

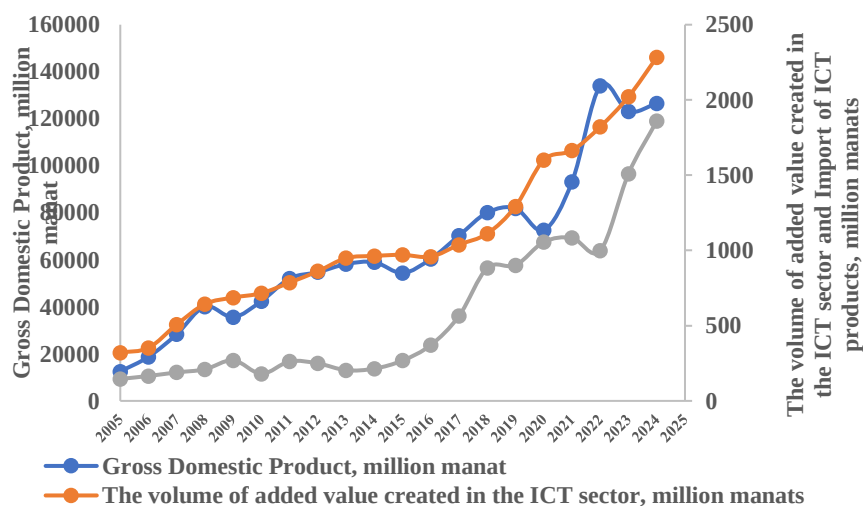
However, considering that a significant share of GDP in Azerbaijan is related to the oil and gas sector, and that the development of other sectors is largely dependent on revenues generated from the oil and gas industry as well as on overall GDP performance, it was decided to investigate the reverse relationship as well. Although the initial estimations were conducted using absolute values, the variables were subsequently transformed into logarithmic form in order to reduce variability and mitigate potential distortions in the economic interpretation of the model coefficients. The estimations were then recalculated using the log-transformed variables.

The data for the variables used in the study were obtained from the official website of the State Statistical Committee of the Republic of Azerbaijan (<https://www.stat.gov.az/>).

	Gross Domestic Product		Value Added in the ICT Sector		ICT Product Imports	
	million AZN	ln	million AZN	ln	million AZN	Ln
	GDP	LGDP	VVICT	LVVICT	IICT	LIICT
2005	12522,5	9,44	320,5	5,77	145,8	4,98
2006	18746,2	9,84	352,6	5,87	165,5	5,11
2007	28360,5	10,25	507,3	6,23	189,5	5,24
2008	40137,2	10,60	643,8	6,47	209,9	5,35
2009	35601,5	10,48	686,8	6,53	270,0	5,60
2010	42465	10,66	715,8	6,57	180,2	5,19
2011	52082	10,86	786,7	6,67	262,6	5,57
2012	54743,7	10,91	861,8	6,76	249,2	5,52
2013	58182	10,97	949,0	6,86	203,8	5,32
2014	59014,1	10,99	963,3	6,87	214,4	5,37
2015	54380	10,90	970,7	6,88	268,6	5,59
2016	60425,2	11,01	958,7	6,87	371,1	5,92
2017	70337,8	11,16	1038,1	6,95	565,1	6,34
2018	80092	11,29	1112,0	7,01	883,8	6,78

2019	81896,2	11,31	1293,3	7,16	901,6	6,80
2020	72578,1	11,19	1600,9	7,38	1055,9	6,96
2021	93203,2	11,44	1663,8	7,42	1083,2	6,99
2022	133972,7	11,81	1822,2	7,51	998,7	6,91
2023	123128,4	11,72	2021,8	7,61	1510,2	7,32
2024	126524,2	11,75	2282,9	7,73	1859,5	7,53

Table 1.
Dynamics of the Model Variables
source: <https://www.stat.gov.az/>



Graph 1.
Dynamics of GDP, VVICT, and IICT
source: <https://www.stat.gov.az/>

The empirical analysis was conducted using OLS, ARDLBT, FMOLS, DOLS, CCR, and VEC.

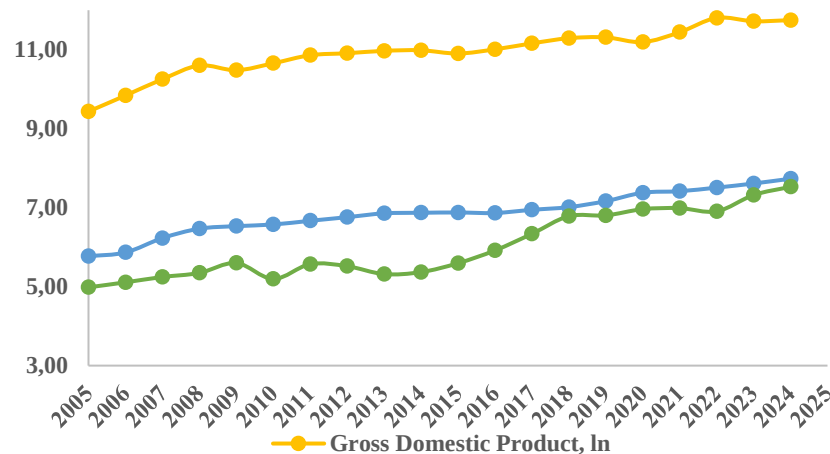
Although OLS is a classical regression technique, its potential to generate spurious results in the presence of non-stationary time series was taken into consideration. Therefore, ARDLBT—an approach that has gained substantial attention in recent empirical research—was employed as the primary estimation method. ARDLBT enables the identification of both short-run and long-run relationships regardless of whether the variables are integrated of order I (0) or I (1).

To verify the robustness, adequacy, and reliability of the long-run estimates obtained from ARDLBT, additional cointegration estimators—FMOLS, DOLS, and CCR—were applied. These methods address issues related to endogeneity and

serial correlation, thereby ensuring consistent and efficient parameter estimation. Finally, VEC was utilized to examine the short-run adjustment mechanisms and the long-run equilibrium relationships among the variables.

The following hypotheses were formulated:

- H1₀ – The volume of value added generated in the ICT sector positively affects the volume of Gross Domestic Product (GDP).
- H2₀ – The volume of ICT product imports positively affects the volume of GDP.
- H3₀ – The volume of value added generated in the ICT sector and the volume of ICT product imports jointly exert a positive effect on the volume of GDP.
- H4₀ – The volume of GDP positively affects the volume of value added generated in the ICT sector.
- H5₀ – The volume of GDP positively affects the volume of ICT product imports.



Graph 2.
Trends in LGDP, LVVICT, and LIICT
Source: <https://www.stat.gov.az/>

Method and Methodology

This study employs the Autoregressive Distributed Lag (ARDL) modelling approach for econometric analysis, as it is particularly suitable for examining both short-run and long-run relationships among variables in relatively small-sample time-series data. One of the principal advantages of the ARDL framework is its

ability to simultaneously estimate both the short-term dynamics and the long-term equilibrium relationships among the variables.

Unlike conventional cointegration techniques, the ARDL approach does not require all variables to be integrated of the same order as a precondition for estimation. Instead, it allows the inclusion of variables that are integrated of order zero, $I(0)$, and order one, $I(1)$, provided that none of the variables is integrated of order two, $I(2)$. Consequently, the ARDL bounds testing procedure enables the investigation of cointegration relationships among variables with mixed orders of integration, a characteristic frequently observed in macroeconomic time-series data (Pesaran et al., 1999).

Compared with the Johansen and Juselius (1990) cointegration methodology, the ARDL approach has been shown to provide more reliable and efficient estimates in studies involving relatively short time-series samples. Another important advantage is that it estimates both short-run and long-run coefficients within a unified modelling framework. Furthermore, unlike the Engle–Granger two-step procedure (Engle & Granger, 1987), the ARDL methodology permits direct hypothesis testing of the estimated long-run coefficients, thereby providing greater flexibility in empirical analysis.

Overall, the ARDL framework offers several methodological advantages over traditional cointegration techniques. In particular, it accommodates variables integrated at $I(0)$ and $I(1)$, either separately or simultaneously, while producing unbiased parameter estimates and valid t-statistics even in the presence of potential endogeneity among regressors. Moreover, selecting the optimal lag structure helps eliminate residual serial correlation and substantially reduces endogeneity concerns.

The short-run dynamics are incorporated into the long-run equilibrium relationship through the Error Correction Model (ECM). The ECM represents a linear transformation of the ARDL model that preserves long-run information while capturing short-run adjustments toward equilibrium. The Error Correction Term (ECT) measures the extent to which deviations from the long-run equilibrium are corrected over time, thereby indicating the speed of adjustment back to equilibrium. For this reason, the ECT coefficient is commonly interpreted as the speed of adjustment parameter. A negative and statistically significant ECT coefficient indicates that the system converges toward its long-run equilibrium following short-run disturbances, providing evidence of a stable long-run cointegration relationship among the variables (Pesaran et al., 2001).

It should be noted, however, that the ARDL bounds testing approach proposed by Pesaran and Shin (1999) and further developed by Pesaran et al. (2001) becomes invalid if any of the variables included in the model is integrated of order two, $I(2)$.

In this study, the Error Correction Model (ECM) is employed to analyse both the short-run dynamics and the long-run equilibrium relationship. Within the ECM framework, the error correction term captures the disequilibrium generated by

short-run shocks and measures the adjustment process through which the system returns to its long-run equilibrium. Accordingly, the long-run dynamics of the endogenous variables are constrained by the short-run adjustment mechanism represented by the ECM. For this reason, the ECM is commonly regarded as the cointegration representation of the conventional ARDL model. The ARDL specification is transformed into a dynamic ECM by incorporating lagged values of the dependent variable, thereby allowing the model to capture both dynamic adjustments and equilibrium correction simultaneously.

According to the adopted research methodology, the ARDL modelling procedure consists of three sequential stages.

Stage I. Testing for cointegration using the Unrestricted Error Correction Model (UECM) framework.

$$\Delta y_{it} = \phi_i (y_{i,t-1} - \beta_i' x_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{i1}^* \Delta x_{i,t-j} + \mu_r + \varepsilon_{it}$$

Where:

- Y – dependent variable;
- X – independent (explanatory) variable;
- Δ – first-difference operator;
- ϕ_i – error correction coefficient of the model;
- β_i – ($k \times 1$) vector of coefficients associated with the explanatory variables;
- $y_{i,t-1} - \beta_i' x_{it}$
= EC_{it} – error correction term (ECT), representing the deviation from the long-run equilibrium;

$$\phi_i = - \left(1 - \sum_{j=1}^p \lambda_{ij} \right), \beta_i = \sum_{j=0}^q \delta_{ij};$$

$$\lambda_{ij}^* = - \sum_{m=j+1}^p \lambda_{im}, j = 1, 2, \dots, p-1;$$

$$\lambda_{ij}^* = - \sum_{m=j+1}^q \delta_{im}, j = 1, 2, \dots, q-1$$

Alternatively, the ARDL–ECM specification can be expressed in the more commonly used simplified form:

$$\Delta Y_t = a_0 + \sum_{j=1}^p \theta_j \Delta Y_{t-j} + \sum_{j=0}^q \gamma_j \Delta x_{t-j} + \lambda_1 Y_{t-1} + \lambda_2 X_{t-1} + \eta_t$$

where:

- λ_1, λ_2 – denote the long-run coefficients (long-run elasticities);
- θ, γ – represent the short-run coefficients (short-run elasticities);
- Δ – denotes the first-difference operator;
- η – is a stochastic error term with zero expected value;
- p, q – denote the optimal lag lengths of the dependent and explanatory variables, respectively.

The optimal lag length for the ARDL model is determined by first identifying the appropriate lag order of the underlying Vector Autoregression (VAR) model using standard information criteria. In this study, the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SC) are employed for lag selection. The results of these criteria indicate that the optimal lag length is one, suggesting that a VAR(1) specification provides the most appropriate representation of the dynamic interactions among the variables. This lag structure achieves an appropriate balance between model goodness-of-fit and parsimony while ensuring a consistent and efficient estimation of both the short-run dynamics and the long-run equilibrium relationship.

If a cointegration relationship among the variables is confirmed, the analysis proceeds to the second stage.

Stage II. Estimation of the Long-Run Relationship

$$Y_t = \sum_{j=1}^p \nu_j Y_{t-j} + \sum_{j=0}^q \xi_j x_{t-j} + \varpi_t$$

Stage III. Estimation of the Short-Run Dynamics Using the Error Correction Model (ECM)

$$\Delta Y_t = c + \sum_{j=1}^p \zeta_j \Delta Y_{t-j} + \sum_{j=0}^q \varrho_j \Delta x_{t-j} + \zeta ECT_{t-1} + \epsilon_t$$

To initiate the estimation procedure, the ARDL Bounds Test is employed to examine the existence of a long-run cointegration relationship by formulating the null and alternative hypotheses. Subsequently, the significance of the lagged regressors is evaluated using both the t-statistic proposed by Banerjee et al. (1998) and the F-statistic introduced by Pesaran et al. (2001). Since many empirical studies

rely on relatively small sample sizes, Narayan (2005) developed adjusted critical values for the F-statistic that are more appropriate for small-sample analyses.

The hypotheses for the cointegration test are specified as follows:

H_0 : No cointegration exists

H_1 : Cointegration exists.

The joint significance of the lagged level variables is assessed using the F-test based on the following hypotheses:

$H_0: v_i = \xi_i = 0$

$H_1: v_i \neq 0, \xi_i \neq 0$

The decision to reject or fail to reject the null hypothesis is based on comparing the calculated F-statistic with the critical bounds values. If the computed F-statistic exceeds the upper critical bound, corresponding to variables integrated of order one, $I(1)$, the null hypothesis is rejected, indicating the existence of a long-run cointegration relationship among the variables. Conversely, if the F-statistic falls below the lower critical bound, corresponding to $I(0)$, the null hypothesis cannot be rejected, implying that no long-run equilibrium relationship exists. When the calculated F-statistic lies between the lower and upper critical bounds, the test result is considered inconclusive, and no definitive inference regarding cointegration can be drawn.

As an additional robustness check, the significance of the long-run relationship is further verified using the t-Bounds test, which is based on the following hypotheses:

$H_0: v_i = \xi_i = 0$

$H_1: v_i < 0$

Diagnostic Tests for the ARDL Model

The validity of the ARDL model requires that the error term (ϵ_t) be serially independent and normally distributed. Accordingly, the Breusch–Godfrey Lagrange Multiplier (LM) Test (Breusch, 1978; Godfrey, 1978) is employed to examine the presence of serial correlation in the residuals, while the Jarque–Bera Test (Jarque & Bera, 1987) is used to assess the normality of the error term.

Furthermore, the Breusch–Pagan–Godfrey Test (Breusch & Pagan, 1979) and the Autoregressive Conditional Heteroskedasticity (ARCH) Test developed by Engle (1982) are applied to detect the presence of heteroskedasticity in the estimated model. These diagnostic procedures ensure that the assumptions underlying the

ARDL framework are satisfied and that the estimated coefficients are statistically reliable.

Stability Analysis of the Model

The dynamic stability of the estimated model is evaluated through recursive residual-based stability tests. In particular, the Cumulative Sum of Recursive Residuals (CUSUM) test and the Cumulative Sum of Squares of Recursive Residuals (CUSUMSQ) test developed by Brown et al. (1975) are employed to assess the stability of the estimated coefficients over the sample period. These tests are widely used in ARDL applications to verify whether the estimated parameters remain stable in the presence of structural changes.

In addition, the Ramsey Regression Specification Error Test (RESET) (Ramsey, 1969; 1974) is performed to evaluate the functional form of the model and to detect potential specification errors arising from omitted variables, incorrect functional forms, or other misspecifications.

A model is considered stable if the CUSUM and CUSUMSQ statistics remain within the 5% critical bounds throughout the sample period. Such results indicate parameter stability and support the robustness of the estimated long-run and short-run relationships.

Alternative Cointegration Estimation Methods: FMOLS, DOLS, and CCR

To enhance the robustness of the empirical findings, the study also employs several alternative cointegration estimation techniques. These include the Fully Modified Ordinary Least Squares (FMOLS) method proposed by Phillips and Hansen (1990), the Dynamic Ordinary Least Squares (DOLS) estimator developed by Stock and Watson (1993), and the Canonical Cointegrating Regression (CCR) approach introduced by Park (1992).

The application of FMOLS, DOLS, and CCR provides an additional robustness check for the long-run estimates obtained from the ARDL Bounds Testing approach. Comparing the results across different cointegration techniques increases confidence in the empirical findings and reduces the likelihood that the conclusions are driven by the limitations of a single estimation method. Therefore, the consistency of results across ARDL, FMOLS, DOLS, and CCR estimators provides stronger evidence regarding the existence and magnitude of long-run equilibrium relationships among the variables.

Unit Root Tests

Prior to estimating the ARDL model, the stationarity properties of the variables are examined using several conventional unit root tests. Employing multiple tests

allows for a more comprehensive assessment of the integration properties of the variables and improves the reliability of the empirical results.

Accordingly, three widely used unit root tests are applied:

- Augmented Dickey–Fuller (ADF) Test (Dickey & Fuller, 1981);
- Phillips–Perron (PP) Test (Phillips & Perron, 1988);
- Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test (Kwiatkowski et al., 1992).

Each of these tests is based on different statistical assumptions and testing procedures. Consequently, the results may either confirm or contradict one another. Moreover, each test possesses specific strengths and limitations. While some tests may be sensitive to structural breaks, serial correlation, or model misspecification, others may be more robust to such issues. Therefore, applying multiple unit root tests provides a more reliable basis for determining the order of integration of the variables and strengthens the validity of subsequent cointegration analysis.

Augmented Dickey–Fuller (ADF) Test

The ADF test can be expressed as follows:

$$\Delta y_t = \beta_0 + \psi t + \beta_1 y_{t-1} + \sum_{i=1}^k \alpha_i \Delta y_{t-i} + \varepsilon_t$$

where:

- Δy_t – denotes the first difference of the variable;
- t – represents the deterministic time trend;
- β_0 – is the intercept term;
- β_1 – measures the presence of a unit root;
- α_i – denotes the coefficients of the lagged first differences;
- ε_t – is a white-noise error term.

The null hypothesis of the ADF test states that the series contains a unit root, whereas the alternative hypothesis indicates stationarity.

Bayer–Hanck Combined Cointegration Test

To provide additional evidence regarding the existence of a long-run equilibrium relationship, the study employs the Bayer–Hanck Combined Cointegration Test developed by Bayer and Hanck (2012). This approach combines the results of several individual cointegration tests into a single Fisher-type framework, thereby increasing the overall power and reliability of cointegration inference.

The Bayer–Hanck procedure integrates the following cointegration tests:

- Engle–Granger (1987);
- Johansen (1988);
- Boswijk Error-Correction-Based Test (1994);
- Banerjee et al. (1998) Error-Correction Test.

The combined test statistic is calculated using Fisher’s (1932) methodology based on the p-values obtained from the individual cointegration tests:

$$\tilde{\chi}_I^2 = -2 \sum_{i \in I} \ln(p_i)$$

where (p_i) denotes the probability value (p –value) associated with each individual cointegration test.

For the combined Engle–Granger and Johansen tests:

$$EG - JOH = -2[\ln(p_{EG}) + \ln(p_{JOH})]$$

For the combined Engle–Granger, Johansen, Boswijk, and Banerjee–Dolado–Mestre tests:

$$EG - JOH - BO - BDM = -2[\ln(p_{EG}) + \ln(p_{JOH}) + \ln(p_{BO}) + \ln(p_{BDM})]$$

where (p) represents the corresponding probability values of the individual tests.

The hypotheses of the Bayer–Hanck cointegration test are specified as follows:

H_0 : no cointegration exists among the variables.

H_1 : a cointegration relationship exists among the variables.

If the calculated Fisher statistic exceeds the critical value reported by Bayer and Hanck (2012), the null hypothesis is rejected, indicating the presence of a long-run cointegration relationship among the variables.

Test Results and Model Estimation Results

Variable	ADF Test				PP Test				KPSS Test		
	Test Value	C	t	N	Test Value	C	t	N	Test Value	C	t
<i>lgdp</i>	-3.43**	x			-3.43**	x			0.12*	x	x
<i>lvvict</i>	-2.07	x			-2.07	x			0.10	x	x
<i>liict</i>	-1.52	x	x		-1.51	x	x		0.15**	x	x
<i>Δlgdp</i>	-2.95***	x	x	x	-3.16***	x	x	x	0.20**	x	x
<i>Δlvvict</i>	-3.13**	x	x		-2.01***	x	x	x	0.13*	x	x
<i>Δliict</i>	-4.68***	x			-4.12***	x	x	x	0.08	x	x

Table. 2.
Unit root test results

Notes:

a: ADF PP and KPSS denote the Augmented Dickey – Fuller Phillips – Perron and Kwiatkowski – Phillips – Schmidt – Shin tests;

b: Maximum lag order is set to three and optimal lag order (k) is selected based on the AIC;

c: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. The critical values for the tests are taken from MacKinnon (1996). Probability based on Kwiatkowski – Phillips – Schmidt – Shin (1992, Table 1)

Estimation period: 2005 – 2024. None means that neither intercept nor trend is included in the test equation. Note that the final unit root test equation can include one of these three: intercept (C), intercept and trend (t) or none of them (N). x indicates that the corresponding option is selected in the final unit root test equation.

According to the results of the unit root tests, the variables employed in the model exhibit different orders of integration. Specifically, *lgdp* was found to be stationary at levels, $I(0)$, according to the ADF, PP, and KPSS tests, with statistical significance ranging from 90% to 99%. In contrast, *lvvict* was determined to be integrated of order one, $I(1)$, based on the ADF, PP, and KPSS tests, with statistical significance between 95% and 99%. Similarly, *liict* was found to be integrated of order one, $I(1)$, according to the ADF and PP tests at the 99% significance level.

Furthermore, none of the variables was found to be integrated of order two, $I(2)$. This finding satisfies the principal prerequisite for applying the Autoregressive Distributed Lag Bounds Testing (ARDLBT) approach and confirms that the ARDL cointegration methodology is appropriate for examining the existence of a long-run equilibrium relationship among the variables.

	Panel A: <i>lgdp/lvvict</i>	Panel B: <i>lgdp/liict</i>	Panel C: <i>lvvict/lgdp</i>	Panel D: <i>liict/lgdp</i>	Panel E: <i>lgdp/lvvict,liict</i>
Model:	(1, 0)	(1, 0)	(2, 0)	(1, 0)	(1, 0, 0)
<i>lgdp</i>	–	–	+0.51***	–0.15	–
<i>lgdp</i> ₍₋₁₎	+0.16	+0.61	–	–	0.16
<i>lvvict</i>	+0.81***	–	–	–	0.81
<i>lvvict</i> ₍₋₁₎	–	–	+0.78***	–	–
<i>lvvict</i> ₍₋₂₎	–	–	–0.44***	–	–
<i>liict</i>	–	+0.09***	–	–	0.005
<i>liict</i> ₍₋₁₎	–	–	–	+1.03***	–
<i>c</i>	+3.64***	+3.74***	–1.09	+1.55	3.63

Table.3.

The results of estimations ARDL Method

Notes: *, **, *** indicate significance at 10%, 5% and 1%, respectively.

According to the initial ARDL estimation results, a one-unit increase in *lvvict* leads to a 0.81-unit (81%) increase in *lgdp*, while a one-unit increase in *liict* results in a 0.09-unit (9%) increase in *lvvict*. Conversely, a one-unit increase in *lgdp* is associated with a 0.51-unit (51%) increase in *lvvict*, whereas a one-unit increase in *liict* leads to a 0.15-unit (15%) decrease in *lvvict*.

Furthermore, based on the multivariate ARDL regression model, the estimated long-run coefficients indicate that a one-unit increase in *lvvict* increases *lgdp* by 0.81 units (81%), consistent with the findings reported in Panel A. In addition, a one-unit increase in *liict* is associated with a 0.005-unit (0.5%) increase in *lgdp*, holding the other explanatory variables constant.

		Panel A: <i>lgdp</i> <i>/lvvict</i>	Panel B: <i>lgdp/liict</i>	Panel C: <i>lvvict/lgdp</i>	Panel D: <i>liict/lgdp</i>	Panel E: <i>lgdp</i> <i>/lvvict,liict</i>
		Model 1	Model 2	Model 3	Model 4	Model 5
<i>F</i>	<i>F^W</i>	+23.781***	+6.410***	+20.931***	+1.437	+14.870***
– Bounds <i>T</i>						
<i>t</i>	<i>t^S</i>	–6.675***	–3.575**	–6.427***	–1.177	–6.444***
– Bounds <i>T</i>						

A:, B:, C:

Null Hypothesis: No levels relationship									
	Asymptotic: ¹		Finite Sample: ²				Test		
	<i>n</i>		<i>n</i> = 35		<i>n</i> = 30		Statistic		
	= 1000		<i>I</i> (0)	<i>I</i> (1)	<i>I</i> (0)	<i>I</i> (1)	<i>I</i> (0)	<i>I</i> (1)	
At the significance level:	10%	4.0 4	4.7 8	+4.22 5	5.05	4.29	5.08	-2. 57	-2.9 1
	5%	4.9 4	5.7 3	5.29	+6.1 75	+5.3 95	6.35	-2. 86	-3.2 2
	2.5%	5.7 7	6.6 8	N/A	N/A	N/A	N/A	-3. 13	-3.5
	1%	6.8 4	7.8 4	7.87	8.96	8.17	9.285	-3. 43	-3.8 2
	<i>D:</i>								
	10%	5.5 9	6.2 6	5.95	6.68	6.01	6.78	-3. 13	-3.4
	5%	6.5 6	7.3 +	7.21	+8.0 55	+8.26 7.36	5	-3. 41	-3.6 9
	2.5%	7.4 6	8.2 7	N/A	N/A	N/A	N/A	-3. 65	-3.9 6
	1%	8.7 4	9.6 3	10.36 5	11.2 95	10.6 05	11.65	-3. 96	-4.2 6
	<i>E:</i>								
	10%	3.1 7	4.1 4	3.393	4.41	3.43 7	4.47	-2. 57	-2.9 1
	5%	3.7 9	4.8 5	4.183	5.33 3	4.26 7	5.473	-2. 86	-3.2 2
	2.5%	4.4 1	5.5 2	N/A	N/A	N/A	N/A	-3. 13	-3.5
	1%	5.1 5	6.3 6	6.14	7.60 7	6.18 3	7.873	-3. 43	-3.8 2

Table 5.

Cointegration test statistics.

*, **, *** indicate significance at 10%, 5% and 1%, respectively.

According to the results of the ARDL Bounds Testing (ARDLBT) cointegration analysis, statistically significant long-run relationships were identified among the variables in Models 1, 2, 3, and 5 at the 1% significance level. These findings provide strong evidence of the existence of cointegration among the variables included in these models. In contrast, Model 4 did not exhibit a statistically

significant long-run cointegration relationship, indicating the absence of a stable long-run equilibrium among the variables specified in that model.

$$\text{Specification with optimal lags, ARDL (1, 0):} \quad lgdp_t = \theta' + \sum_{i=1}^1 \eta'_i lgdp_{t-i} + \sum_{i=0}^0 \vartheta'_i lvvict_{t-i} + u_t$$

Variables	OLS	ARDL	CCR	DOLS	FMOLS	VEC
<u><i>lgdp/lvvict</i></u>						
Panel A1: Estimated Long – Run Coefficients						
<i>lvvict</i>	+1.15***	+0.97***	+1.12***	+1.13***	+1.09***	+0.91***
<i>c</i>	+3.07***	+4.33***	+3.26***	+3.22***	+3.49***	+4.66
<i>R</i> ²	+0.88	+0.87	+0.85	+0.83	+0.85	+0.35
<i>AdjR</i> ²	+0.87	+0.85	+0.83	+0.78	+0.84	+0.31
<i>D – W</i>	+1.39	+1.92				
<i>AIC</i>	–0.93	–1.29				–0.45
<i>SC</i>	–0.83	–1.14				–0.34
Panel B1: Residuals Diagnostics Tests Results						
χ^2_{SC}	3.32 [0.18]	8.65 [0.01]				
χ^2_{HETR}	3.46 [0.06]	0.06 [0.96]				
χ^2_{ARCH}	0.15 [0.69]	1.95 [0.16]				
<i>JB_N</i>	0.58 [0.75]	0.60 [0.74]				
<i>F_{FF} t – st</i>	1.97 [0.06]	0.32 [0.75]				
<i>CUSUM</i>	<i>Stability</i>	<i>Stability</i>				
<i>CUSUMS</i>	<i>Stability</i>	<i>Stability</i>				

$$\text{Specification with optimal lags, ARDL (1, 0):} \quad lgdp_t = \theta' + \sum_{i=1}^1 \eta'_i lgdp_{t-i} + \sum_{i=0}^0 \vartheta'_i liict_{t-i} + u_t$$

<u><i>lgdp/liict</i></u>						
Panel A2: Estimated Long – Run Coefficients						
<i>liict</i>	+0.38*	+0.22	+0.39	+0.31	+0.35	+0.32
<i>c</i>	+8.54***	+9.65***	+8.59***	+9.20***	+8.84***	+8.92
<i>R</i> ²	+0.24	+0.72	+0.06	+0.39	+0.09	+0.47

<i>AdjR</i> ²	+0.19	+0.68	+0.01	+0.19	+0.03	+0.44
<i>D – W</i>	+0.43	–0.35				
<i>AIC</i>	+0.90	–0.47				–0.65
<i>SC</i>	+1.00	+1.48				–0.55
Panel B2: Residuals Diagnostics Tests Results						
χ^2_{SC}	8.00 [0.02]	2.45 [0.29]				
χ^2_{HETR}	4.23 [0.04]	1.91 [0.38]				
χ^2_{ARCH}	7.00 [0.01]	0.32 [0.56]				
JB_N	0.99 [0.60]	0.84 [0.65]				
$F_{FF} \ t – st$	1.20 [0.24]	0.01 [0.98]				
<i>CUSUM</i>	<i>Stability</i>	<i>Stability</i>				
<i>CUSUMS</i>	<i>Stability</i>	<i>Stability</i>				
Specification with optimal lags, ARDL (2, 0): $lvvict_t = \theta' + \sum_{i=1}^2 \eta'_i lvvict_{t-i} + \sum_{i=0}^0 \vartheta'_i lgdp_{t-i} + u_t$						
<i>lgdp/liict</i>						
Panel A3: Estimated Long – Run Coefficients						
<i>lgdp</i>	+0.76***	+0.77***	+0.82***	+0.94***	+0.87***	+0.92***
<i>c</i>	–1.54*	–1.63*	–2.08**	–3.51*	–2.70*	–3.34
<i>R</i> ²	+0.88	+0.92	+0.86	+0.87	+0.86	+0.45
<i>AdjR</i> ²	+0.87	+0.90	+0.85	+0.83	+0.85	+0.34
<i>D – W</i>	+1.35	+2.20				
<i>AIC</i>	–1.24	–1.86				–0.89
<i>SC</i>	–1.32	–2.03				–0.70
Panel B3: Residuals Diagnostics Tests Results						
χ^2_{SC}	+4.37 [0.12]	+6.52 [0.03]				
χ^2_{HETR}	+1.18 [0.27]	+2.97 [0.39]				
χ^2_{ARCH}	+0.51 [0.47]	+0.63 [0.42]				
JB_N	+0.30 [0.86]	+0.68 [0.71]				
$F_{FF} \ t – st$	+1.42 [0.17]	+2.15 [0.05]				
<i>CUSUM</i>	+ <i>Stability</i>	+ <i>Stability</i>				

<i>CUSUMS</i>	<i>+Stability</i>	<i>+Stability</i>
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Specification with optimal lags, ARDL (1, 0):

$$liict_t = \theta' + \sum_{i=1}^1 \eta'_i liict_{t-i} + \sum_{i=0}^0 \vartheta'_i lgdp_{t-i} + u_t$$

<i>liict/lgdp</i>						
Panel A4: Estimated Long – Run Coefficients						
<i>lgdp</i>	+0.62	+4.28	+0.73	+0.64	+0.88	+2.76***
<i>c</i>	−0.84	−43.34	−2.11	−1.09	−3.71	−24.06
<i>R</i> ²	+0.24	+0.79	+0.16	+0.18	+0.14	+0.11
<i>AdjR</i> ²	+0.19	+0.77	+0.11	−0.09	+0.08	−0.08
<i>D – W</i>	+0.33	+2.45				
<i>AIC</i>	+1.48	+0.28				+0.23
<i>SC</i>	+1.40	+0.16				0.43
Panel B4: Residuals Diagnostics Tests Results						
χ^2_{SC}	+13.63 [0.00]	+2.04 [0.36]				
χ^2_{HETR}	+5.07 [0.02]	+0.99 [0.61]				
χ^2_{ARCH}	+3.18 [0.07]	+0.01 [0.92]				
JB_N	+1.35 [0.51]	+0.33 [0.85]				
$F_{FF} \ t - st$	+0.02 [0.99]	+1.39 [0.26]				
<i>CUSUM</i>	<i>Stability</i>	<i>Stability</i>				
<i>CUSUMS</i>	<i>No – stability</i>	<i>Stability</i>				

$$lgdp_t = \theta' + \sum_{i=1}^1 \eta'_i lgdp_{t-i} + \sum_{i=0}^0 \vartheta'_i liict_{t-i} + \sum_{i=0}^0 \vartheta'_i liict_{t-i} u_t$$

Specification with optimal lags, ARDL (1, 0, 0):

<i>lgdp/lvvict, liict</i>						
Panel A5: Estimated Long – Run Coefficients						
	OLS	ARDL	CCR	DOLS	FMOLS	VEC
<i>lvvict</i>	+1.14***	+0.96***	+1.16***	+1.48***	+1.15***	+1.24***
<i>liict</i>	+0.009	+0.005	−0.06	−0.17*	−0.05	−0.07
<i>c</i>	+3.07***	+4.33***	+3.39***	+1.83*	+3.36***	+2.87

R^2	+0.88	+0.87	+0.83	+0.88	+0.84	+0.34
$AdjR^2$	+0.87	+0.85	+0.81	+0.77	+0.82	+0.14
$D - W$	+1.39	+1.92				
AIC	-0.69	-0.99				
SC	-0.81	-1.15				

Panel B5: Residuals Diagnostics Tests Results

χ_{SC}^2	+3.33 [0.19]	+8.68 [0.01]
χ_{HETR}^2	+6.13 [0.05]	+1.73 [0.63]
χ_{ARCH}^2	+0.19 [0.66]	+1.90 [0.17]
JB_N	+0.72 [0.70]	+0.68 [0.71]
$F_{FF} t - st$	+1.95 [0.07]	+0.32 [0.75]
$CUSUM$	+Stability	+Stability
$CUSUMS$	+Stability	+Stability

Table 6.

The results of estimations Long – Run

Notes: The dependent variable is *reer*; residuals diagnostics tests results are from the selected ARDL specifications; χ_{SC}^2 , χ_{HETR}^2 and χ_{ARCH}^2 denote chi-squared statistics to test the null hypotheses of no serial correlation and no heteroscedasticity in the residuals; JB_N and F_{FF} indicate Jarque – Bera and no functional form misspecification statistics to test the null hypotheses of the normal distribution and no functional misspecification, respectively; probabilities are in brackets, and standard errors are in parentheses; ECT is the Error Correction Term, i.e., the residuals of the long-run equation. *, **, *** indicate significance at 10%, 5% and 1%, respectively. Estimation period: 2005 – 2024.

The estimated long-run coefficients indicate that a one-unit increase in *lvvict* is associated with an increase in *lgdp* ranging from 0.91 to 1.15 units (91%–115%), with the relationship being statistically significant at the 1% significance level across the estimated models. This finding suggests that *lvvict* exerts a strong and positive long-run effect on economic growth.

By contrast, a one-unit increase in *liict* is associated with an increase in *lgdp* ranging from 0.22 to 0.38 units (22%–38%). However, this relationship is generally statistically insignificant across the estimated long-run models, with the exception of the Ordinary Least Squares (OLS) estimation, where the coefficient is statistically significant at the 10% significance level. Therefore, although the estimated coefficient is positive, the empirical evidence provides only limited support for a statistically significant long-run impact of *liict* on *lgdp*.

	<i>Engle – Granger</i>		<i>Phillips – Ouliaris</i>	
	<i>tau – statistic</i>	<i>z – statistic</i>	<i>tau – statistic</i>	<i>z – statistic</i>
Model 1	–4.00**	–32.63***	–4.17*	–14.77
Model 2	–2.99	–7.26	–2.99	–8.30
Model 3	–3.64*	–32.38***	–3.30	–14.00
Model 4	–0.61	–1.76	–0.61	–1.70
Model 5	–3.98*	–32.69***	–4.16*	–14.80

Table 7.

The results of Cointegration Test: Engle – Granger and Phillips – Ouliaris

Notes: *, **, *** indicate significance at 10%, 5% and 1%, respectively.

To verify the robustness and reliability of the ARDL Bounds Testing (ARDLBT) cointegration results, additional cointegration estimation techniques, including Canonical Cointegrating Regression (CCR), Dynamic Ordinary Least Squares (DOLS), and Fully Modified Ordinary Least Squares (FMOLS), were employed. The robustness of the estimated long-run relationships was further assessed using the Engle–Granger and Phillips–Ouliaris residual-based cointegration tests.

The empirical results indicate that Model 1 satisfies the Engle–Granger cointegration test at the 5% significance level based on the tau-statistic and at the 1% significance level based on the z-statistic. Similarly, Models 3 and 5 pass the Engle–Granger test at the 10% significance level according to the tau-statistic and at the 1% significance level according to the z-statistic. Furthermore, Models 1 and 5 satisfy the Phillips–Ouliaris cointegration test at the 10% significance level based on the tau-statistic.

Overall, the consistency of the results obtained from the ARDLBT, CCR, DOLS, FMOLS, Engle–Granger, and Phillips–Ouliaris approaches provides robust evidence supporting the existence of stable long-run cointegration relationships among the variables in the respective models.

Model:	Panel A:	Panel B:	Panel C:	Panel D:	Panel E:
	<i>lgdp/lvict</i>	<i>lgdp/liict</i>	<i>lvict/lgdp</i>	<i>liict/lgdp</i>	<i>lgdp/lvict, liict</i>
	(1, 0)	(1, 0)	(2, 0)	(1, 0)	(1, 0, 0)
<i>CointEq₍₋₁₎</i>	–0.84***	–0.39**	–0.66***	–0.26	–0.83
<i>Δlvict₍₋₁₎</i>	–	–	+0.44***	–	–
<i>@trend</i>	–	–	–	+0.03	–
<i>c</i>	+3.64***	+3.74**	–1.09***	+3.05	+3.63
<i>t – Bounds Test</i> <i>t^S</i>	–7.108***	–3.690**	–6.697***	–1.751	–7.110***

R^2	+0.75	+0.44	+0.83	+0.19	+0.75
$AdjR^2$	+0.73	+0.41	+0.81	+0.09	+0.73
$D - W$	+1.92	+1.48	+2.20	+2.18	+1.92
AIC	-1.29	-0.51	-2.17	-0.03	-1.39
SC	-1.38	-0.58	-2.02	+0.11	-1.29

Table 8.

The results of estimations Short – Run

Notes: *, **, *** indicate significance at 10%, 5% and 1%, respectively.

With respect to the short-run dynamics, the estimation results indicate that the intercept (constant term) does not exert a statistically significant effect on the dependent variable in any of the estimated models.

Among the explanatory variables, only Model 3 exhibits a statistically significant autoregressive effect, whereby the lagged value of $lvvict$ at the first lag significantly influences its current value, indicating the presence of short-run persistence in the series.

The estimated coefficient of the error correction term, $CointEq(-1)$, is negative in all estimated models, consistent with the theoretical expectations of the Error Correction Model (ECM). Moreover, the coefficient is statistically significant in three models—Models 1 and 3 at the 1% significance level, and Model 2 at the 5% significance level. The negative and statistically significant error correction coefficient confirms the existence of a stable long-run equilibrium relationship and indicates that short-run deviations from equilibrium are gradually corrected over time. In other words, the estimated adjustment mechanism ensures that the system converges toward its long-run equilibrium following short-term shocks.

		Model 1	Model 2	Model 3	Model 4	Model 5
Engle – Granger	$t - St$	-4.00**	-2.50	-3.65*	-0.37	-3.98*
Johansen	$t - St$	+16.08*	+11.84	+16.08*	+11.84	+19.13
Banerjee	$t - St$	-4.55***	-3.47*	-3.72**	+0.94	-4.20**
Boswijk	$t - St$	+21.52***	+12.05*	+14.86**	+1.92	+19.51**
EG – J:	$F - St$	+16.70**	+6.43	+14.58*	+3.90	+12.13*
EG – J – Ba – Bo	$F - St$	+45.23***	+20.29*	+32.03*	+4.29	+32.01*
5% critical 1	11.229	1% critical 1	17.304	10% critical 1	8.678	
5% critical 1	21.931	1% critical 1	33.969	10% critical 1	16.964	

5% critical 2	11.229	1% critical 2	17.304	10% critical 2	8.678
5% critical 2	21.931	1% critical 2	33.969	10% critical 2	16.964

Table 9
The results of Bayer-Hank combined cointegration test

Finally, the results of the combined cointegration analysis provide further evidence supporting the existence of long-run equilibrium relationships among the variables. Specifically, the Engle–Granger cointegration test confirms cointegration for Model 1 at the 5% significance level and for Model 5 at the 10% significance level. The Johansen cointegration test indicates statistically significant cointegration for Models 1 and 3 at the 10% significance level. Similarly, both the Boswijk and Banerjee et al. error-correction-based cointegration tests confirm the presence of cointegration for Model 1 at the 1% significance level, for Models 3 and 5 at the 5% significance level, and for Model 2 at the 10% significance level.

Furthermore, the combined Engle–Granger–Johansen (EG–J) statistic is statistically significant for Model 1 at the 5% significance level and for Models 3 and 5 at the 10% significance level. Likewise, the comprehensive Engle–Granger–Johansen–Banerjee–Boswijk (EG–J–Ba–Bo) combined statistic is significant at the 1% significance level for Model 1 and at the 10% significance level for Models 2, 3, and 5.

Overall, the consistency of the individual and combined cointegration test results provides strong empirical evidence supporting the existence of stable long-run equilibrium relationships among the variables included in the estimated models. These findings further reinforce the robustness of the ARDL Bounds Testing results and confirm the reliability of the estimated long-run relationships.

Discussion and conclusion

The existing body of literature and practical evidence consistently indicate that digitalization, the expansion of information and telecommunication activities, increasing investment in the digital sector, and improvements in the sector's economic and financial performance generally contribute positively to overall economic development and, in particular, to economic growth. This positive relationship has been documented in numerous empirical studies, especially for developed economies where digital transformation has become one of the principal drivers of productivity and sustainable economic growth.

However, the empirical findings of the present study do not fully support this conventional view. Instead, the estimated relationships suggest that the contribution of digitalization to economic growth in Azerbaijan remains relatively limited and, in some model specifications, statistically insignificant. These findings imply that

the economic benefits of digital transformation have not yet been fully translated into sustained long-run economic growth.

Our results are broadly consistent with the findings of Irtysheva, I. and co-authors (2021), who examined the impact of digitalization on Ukraine's economic development. Their study evaluated the effects of the financial performance of enterprises operating in the information and telecommunications sector, capital investment, foreign direct investment, and the development of digitally transformed economic sectors on real GDP. The authors concluded that Ukraine continues to lag behind developed economies in the production of information and communication technologies and related equipment and remains highly dependent on imports. Consequently, the contribution of digitalization to economic growth has been constrained by structural weaknesses within the domestic economy.

Similarly, the findings of the present study are consistent with those reported by Aleksandrova, A. et al. (2022), who investigated the relationship between digitalization and economic growth in Russia. Their empirical evidence suggests that the existing level of digital readiness among the population, together with prevailing macroeconomic conditions, has limited the ability of digital technologies to generate substantial improvements in the rate of economic growth.

Furthermore, the short-run results obtained in this study are broadly in line with the conclusions of Jangid, H. et al. (2024), who found evidence of a negative short-run relationship between digitalization and economic growth across the G20 economies. This suggests that the economic benefits of digital transformation may require a longer adjustment period before becoming fully reflected in macroeconomic performance.

The similarity between our findings and those reported for Ukraine and Russia can largely be explained by the dominant role of other growth determinants in these economies. In Russia, economic growth continues to be heavily influenced by the energy sector, particularly oil and gas production. In Ukraine, agriculture, manufacturing, heavy industry, and mining remain among the primary drivers of economic growth. Under such circumstances, the contribution of digitalization to aggregate economic performance becomes relatively less pronounced.

In contrast, the findings differ from those reported by Neffati, M. (2025), who concluded that digitalization contributes significantly to economic growth in both the short run and the long run in Saudi Arabia. This difference may be attributed to the country's extensive investment in information and communication technologies, advanced digital infrastructure, favourable business environment, and successful implementation of digital transformation strategies aimed at attracting both domestic and foreign investment. These structural advantages have enabled Saudi Arabia to convert digital investments into measurable gains in economic performance.

The empirical evidence for Azerbaijan suggests a different pattern. Although expenditure on digitalization, value added generated by the information and communication technology sector, and imports of digital technologies have increased over time, their contribution to economic growth remains relatively modest. One possible explanation is that Azerbaijan's economic growth continues to be predominantly driven by the hydrocarbon sector. Consequently, the macroeconomic impact of digitalization is partially overshadowed by the dominant influence of oil and gas revenues, reducing the observable contribution of digital transformation to *gdp* growth.

Overall, the empirical analysis indicates that the variables exhibit positive and, in most cases, statistically significant relationships when examined individually, both in their original values and in logarithmic form. However, when the joint effects of multiple explanatory variables are estimated within the multivariate models, the impact of *iict* on *gdp* and *LICT* on *LGDP* becomes statistically insignificant and, in several specifications, negative. These findings suggest that the economic benefits of digitalization in Azerbaijan have not yet reached a level sufficient to generate a robust and statistically significant contribution to long-run economic growth.

With regard to the research hypotheses, the empirical results provide support for the majority of the proposed hypotheses. The only hypothesis that is not fully confirmed is *H3*, which postulated a positive and statistically significant impact of information and communication technology investment on economic growth within the multivariate framework. The estimated coefficients indicate that, after controlling for other explanatory variables, the effects of *iict* on *gdp* and *liict* on *lgdp* are weak, statistically insignificant, and, in some model specifications, negative. This outcome suggests that increasing investment in the digital sector alone may not be sufficient to stimulate economic growth unless accompanied by complementary institutional reforms, technological innovation, improvements in human capital, and greater efficiency in the utilization of digital infrastructure.

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