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How does digitalization enhance sustainable economic development? The case of Azerbaijan and Hungary

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ABSTRACT

Understanding the economic consequences of digitalisation is essential for designing policies that foster inclusive and sustainable development, particularly within emerging and transition economies. This research explores the influence of digitalisation on sustainable economic progress in Azerbaijan and Hungary, utilising annual data spanning from 2000 to 2023. Employing a hybrid methodological approach, the study integrates conventional econometric analysis (VECM) with supervised machine learning techniques (ARIMA and XGBRegressor) to provide a comparative assessment of the economic impacts resulting from digital transformation. The empirical results indicate that, in the short term, variables associated with information and communication technology (ICT) do not exert a statistically significant effect on economic growth. This finding suggests that the economic benefits of digitalisation may take time to materialise. Conversely, in the long term, digitalisation demonstrates a notable influence on GDP per capita in both nations. Specifically, in Azerbaijan, a 1 percent rise in Computer, communications, and other services (CCS) correlates with a decrease of $173.68 in GDP per capita, while Hungary experiences a reduction of $516.28 under similar conditions. Additionally, mobile subscriptions (MSC) and the contribution of high-tech manufacturing value-added (MHTMV) are associated with adverse effects on Azerbaijan's economic development. Forecasts generated through machine learning further predict economic expansion in Hungary over the coming five years, whereas Azerbaijan is projected to encounter economic contraction. The study concludes by underscoring the importance of long-term policy measures centred on digital infrastructure, innovation potential, and human capital enhancement in order to optimise the economic outcomes of digital transformation.

1. Introduction

In recent years, sustainability has emerged as a guiding principle for framing both national and international development strategies. It is instrumental in facilitating efficient allocation of resources to attain targeted outcomes across social, economic, and environmental dimensions. Furthermore, sustainability contributes to improved quality of life by promoting access to

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education, reducing income disparities, ensuring social equity, enhancing food security, and supporting livelihoods. Realising sustainability necessitates coordinated efforts spanning policy, technological innovation, and institutional support, which is particularly critical in the context of developing nations. Among the catalysts of sustainable development in the 21st century, digitalisation has gained increasing prominence. It entails the integration of digital technologies into economic, administrative, and social systems to improve efficiency, innovation, and accessibility [60]. As a consequence of digitalisation, digital transformation significantly alters the structure and functioning of economies by enabling data-informed policymaking, intelligent automation, continuous monitoring, and citizen-oriented service delivery.

For developing countries, digitalisation presents both significant opportunities and considerable challenges. While it has the potential to accelerate economic growth and modernise public institutions, limitations in digital infrastructure and human capital frequently hinder equitable implementation. These complexities render the relationship between digitalisation and sustainable development both theoretically significant and practically relevant. The interconnectedness of digitalisation, sustainability, and economic growth is increasingly acknowledged in academic research and policy discussions [31; 43; 59]. Schumpeterian innovation theory underscores the role of technological disruptions in prompting long-term structural shifts and economic regeneration [74]. Similarly, endogenous growth theory highlights the capacity of digital investments to enhance productivity and support sustainable development through human capital, research, and innovation [72]. Sustainable digitalisation, as posited by socio-technical systems theory, requires a balance between technological advancement, institutional support, and human adaptation [22].

To address the practical dimensions of sustainable digitalisation, the Digitainability Assessment Framework (DAF) was introduced as a tool to evaluate the impact of digital interventions on the Sustainable Development Goals (SDGs), drawing on the Theory of Change (ToC). DAF aims to assist developers, policymakers, and stakeholders by providing a comprehensive impact assessment of digital products and services while identifying opportunities for enhancement [25]. Nevertheless, empirical validation of these conceptual models remains scarce within the context of emerging and post-socialist economies. This study seeks to bridge this gap by exploring the digitalisation–sustainability relationship through an empirical assessment of digitalisation's impact on sustainable economic development in two contrasting national settings: Azerbaijan and Hungary. These countries were selected due to their divergent economic systems and distinct digital policy approaches. Azerbaijan has prioritised energy efficiency, e-governance, and economic diversification, whereas Hungary has focused on advancing smart agriculture, renewable energy, and Industry 4.0 technologies. As a result, this comparative analysis provides an opportunity to:

1) Examine how varying institutional and economic contexts influence the effectiveness of digitalisation in fostering sustainable economic outcomes;
2) Derive contextual insights that are applicable to both EU-aligned (Hungary) and transition economies (Azerbaijan).

Hungary has achieved substantial advancements in its digital economy, driven by national initiatives such as the Digital Success Programme, the Digital Education Strategy of Hungary, and the National Digitalisation Strategy 2022–2030. These efforts have supported an estimated annual GDP growth rate of 5 percent between 2015 and 2021. Consequently, the digital sector now represents approximately 10 percent of Hungary's GDP, with the ICT industry employing 4.8 percent of the national workforce as of 2021. In contrast, while Azerbaijan's digital transformation is relatively more modest, it has made meaningful contributions since 2016. The adoption of advanced technologies has accounted for 1.8 percent of GDP growth Bank [7], in addition to reducing administrative expenses by 25 percent and enhancing rural access to public services by 35 percent

[17]. These developments underscore the growing relevance of digitalisation in Azerbaijan's economic and social evolution.

Despite the proliferation of research on digital transformation, most studies have concentrated on advanced economies. Few investigations, particularly those integrating both econometric and machine learning approaches, have assessed the economic effects of digitalisation in EU-associated and transition countries. While the global narrative increasingly advocates for digital transformation, empirical consensus regarding its direct impact remains limited for small and medium-sized economies. This ambiguity arises from differing developmental paths and national contexts. The nexus between digitalisation and economic growth is highly complex, temporally sensitive, and context-dependent. This is particularly evident in the cases of Azerbaijan and Hungary, where unique political settings, institutional structures, and technological priorities shape digital outcomes.

The overarching aim of this study is to evaluate the role of digitalisation in driving sustainable economic development in Azerbaijan and Hungary. The specific objectives include:

1) Constructing a robust indicator system to measure digitalisation and economic sustainability;
2) Investigating both the short-term and long-term effects of digitalisation on sustainable economic development through econometric modelling;
3) Enhancing predictive accuracy using classical machine learning models to generate tailored economic forecasts;
4) Formulating policy recommendations informed by empirical evidence to optimise economic returns from digital investments.

This research contributes to the literature by offering a comparative, data-driven analysis of two nations with contrasting digital strategies and economic profiles. It advances methodological rigour by employing machine learning techniques to improve the accuracy and policy relevance of development forecasts. The findings are of significant value to national policymakers, international organisations, and researchers concerned with digital economic transformation, as they offer actionable insights for enhancing the efficacy of digital investments, advancing sustainability goals, and reinforcing economic resilience.

The remainder of this paper is structured as follows. Section 2 provides a detailed review of the literature, highlighting key theoretical frameworks and critically evaluating empirical research on digital transformation and sustainability across diverse national contexts. Section 3 outlines the research methodology, including the development of the indicator system, data sources, and analytical tools. It also presents an overview of the econometric and machine learning techniques utilised in the study. Section 4 presents the empirical findings and discussion, offering comparative insights for Azerbaijan and Hungary. This includes descriptive statistics, model outputs, and analysis under two distinct scenarios, followed by a discussion on theoretical and practical implications in relation to existing scholarship and policy relevance. The final section summarises the main findings, presents evidence-based recommendations, and suggests directions for future research.

2. Literature Review

A central aim of sustainable economic development is to ensure that vulnerable and economically marginalised populations can access secure and enduring livelihood opportunities. Over the long term, the development of macroeconomic strategies and the creation of incentive structures for the efficient use of natural resources provide a solid framework for promoting policies consistent with the principles of sustainable growth [10]. One of the core components underpinning sustainable economic development is green growth [9; 58; 82]. Nonetheless, green growth by itself is insufficient to achieve comprehensive sustainability if the degradation and depletion of global ecosystems remain unaddressed. Continued reliance on ecological systems to meet human demands contributes to the erosion of crucial ecosystem services, thereby jeopardising the long-term viability of both environmental and economic systems [8]. Emerging scholarship highlights that achieving sustainability necessitates the integration of multiple dimensions, including digitalisation, environmentally conscious innovation, and sustainable economic strategies. Transitioning towards a sustainable economic model entails the adoption of advanced technological solutions, the promotion of production methods that minimise resource consumption, and the implementation of policies that simultaneously support economic expansion and ecological conservation [73; 82].

2.1 Empirical Studies on Digitalisation and Sustainable Development

Existing scholarly evidence demonstrates that digitalisation serves as a highly influential instrument for advancing sustainable development. It contributes to enhanced efficiency, profitability, and long-term sustainability across a range of sectors and industries [12; 39; 41; 51; 64; 83]. As natural resources become increasingly scarce, their prudent management and equitable allocation are recognised as central to sustainable development objectives [54]. In this regard, digital transformation plays a pivotal role by improving the utilisation of natural assets through data-driven strategies and optimisation processes [18; 93]. Within the context of the digital era, countries across the globe are prioritising the implementation of strategic policies that support the attainment of Global Sustainable Development (GSD). GSD is widely referenced in academic literature and is defined as a developmental process that satisfies current socio-economic needs while safeguarding the well-being of future generations [40].

Given its importance, identifying and analysing the determinants of sustainability at the global scale remains a vital concern in both academic inquiry and policy design. In an effort to explore the linkage between digitalisation and global sustainable development across 34 countries, a comparative analysis was conducted using a set of composite indices developed via the z-score method. These included the Economic Development Index, Social Development Index, Environmental Sustainability Index, and Information and Communication Technology Index. The empirical findings indicated that digitalisation significantly enhanced both economic and social development indicators, with economic gains averaging 1.8 percent, largely due to the expansion of digital services. However, a concurrent 0.6-point decline in environmental sustainability metrics was also observed, highlighting the urgent need for environmentally sensitive digital policy frameworks [76].

In a similar study Lei et al. [43] examined OECD countries using panel regression techniques to evaluate the impact of digital investment on sustainability metrics. Their analysis established a robust long-term association, with ICT investments resulting in a 2.4 percent rise in GDP per capita and a 1.5 percent increase in the Human Development Index. The policy implications of advancing digital technologies to address major sustainability challenges were also explored by [68]. Analysing data from 20 countries (comprising both developed and developing nations), their findings revealed that in 85 percent of cases, digital infrastructure development was positively associated with economic growth. Jiao and Sun [36] applied time-series models to assess the impact of digital infrastructure in China, reporting that a 1 percent increase in digital investment led to a 0.9 percent rise in GDP over the long term. Complementing this, Zhang et al. [92] emphasised the sectoral contributions of digital finance and e-commerce, which significantly supported regional economic convergence.

Trade activities, particularly imports and exports, continue to play a key role in economic performance by influencing industrial growth, trade balance, and national income. Accordingly, the international exchange of goods, services, and advanced technologies remains a prominent subject in economic research [38; 49; 50]. However, findings from empirical investigations involving both developing and developed economies suggest that high-technology exports do not exert a statistically significant influence on GDP growth. Instead, the studies revealed unidirectional causality running from GDP growth to high-tech exports [77]. Beyond digitalisation alone, the broader concept of the digital economy is increasingly being examined for its contribution to sustainability.

For instance, an empirical analysis employing the Cobb–Douglas production function in China found that the digital economy accounted for approximately 1.6 percent of total factor productivity growth [47]. Further, the integration of 'data elements' into neoclassical and new structural general equilibrium models revealed that digitalisation positively influenced economic growth in developing countries. These studies emphasise the importance of tailoring digital strategies to align with country-specific developmental conditions and policy environments [34]. Luo et al. [46] found that the development of the digital economy significantly fosters green innovation in China, suggesting that digitalisation not only supports economic performance but also contributes to sustainable development outcomes. Moreover, subnational or regional variations in digitalisation also demonstrate considerable influence on economic outcomes, as shown in recent research on regional digital transitions [47].

2.2 *Research Gaps and Study Contribution*

A growing body of research has explored the influence of digitalisation on economic performance, with particular emphasis on its sectoral impacts and its broader contribution to national development through the digital economy. These studies highlight the transformative potential of digitalisation in both public and private sectors, indicating its role in boosting productivity, fostering innovation, and introducing novel operational processes. However, despite these insights, much of the literature remains fragmented. Many studies concentrate on isolated aspects or mechanisms of digitalisation, lacking an integrative framework that holistically captures the multifaceted relationship between digital transformation and sustainable economic development.

In addition, although existing theoretical and empirical literature recognises the benefits associated with digitalisation, it often overlooks or underrepresents the institutional and structural challenges involved. Key issues such as data privacy, regional disparities in digital competence, inequitable access to digital infrastructure, and the substantial initial investment required for digital transformation are frequently insufficiently addressed. As a result, many of the policy suggestions derived from prior studies are either overly narrow or fail to reflect the diverse capacities of countries that are situated at different stages of digital advancement. A further limitation lies in the methodological choices employed. Many studies rely solely on conventional econometric tools and short-term associations without exploring the long-term predictive capacity of digitalisation using advanced modelling approaches, such as machine learning. The absence of comparative analytical frameworks that assess EU-aligned and transition or resource-dependent economies also restricts the broader applicability and contextual relevance of their findings. In light of these limitations, the present study seeks to address conceptual, empirical, and predictive gaps in the literature as follows:

2.2.1 Conceptual Contribution:

A tailored indicator system is developed, linking measurable components of sustainable economic development with core elements of digitalisation, such as ICT infrastructure, digital trade, and digital literacy;

2.2.2 *Empirical Contribution*

The study offers a robust, multi-faceted analysis of the digitalisation–development nexus in Azerbaijan and Hungary by combining supervised machine learning with both short-term and long-term econometric models;

2.2.3 *Predictive and Policy Contribution*

By forecasting developmental trajectories and examining current digital-economic relationships, the research delivers evidence-based policy recommendations designed to inform and shape sustainable digital strategies across transition and EU-member economies.

3. Research Methodology

A critical examination of existing literature and conceptual models affirms the significant role that digitalisation plays in advancing sustainable economic development. Accurately evaluating this impact necessitates the use of ICT indicators that capture the status of digital infrastructure, levels of adoption, and the extent of technology-driven economic activities. As sustainable economic growth seeks to fulfil societal demands while safeguarding natural resources and maintaining ecological balance, digitalisation within this framework must be assessed across several fundamental dimensions, including productivity enhancement, technological innovation, social inclusion, environmental sustainability, and operational efficiency. Based on these considerations, this study identifies a set of ICT indicators that serve as core components of digitalisation, which are presented in Table 1.

Table 1
ICT Indicators

Indicator	Unit	Referenced in Existing Literature
Internet Penetration Rate (IPR)	A continuous variable expresses the percentage of individuals using the Internet within the total population.	ITU [32] Harb [28] Czernich et al. [15]
ICT Service Exports (ICT_SE)	A continuous variable expresses the share of ICT service exports as a percentage of total service exports.	Tian and Son [80] Vu [84]
ICT Goods Imports (ICT_GI)	A continuous variable expresses the share of ICT goods imports as a percentage of total goods imports.	Roger et al. [71] Yoon [90] Dedrick et al. [16]
Computer, Communications, and Other Services (CCS)	A continuous variable. It represents the share of computer, communications, and other services in total commercial service exports and is expressed as a percentage	Li et al. [44] Mulenga and Mayondi [52]
Medium and High-Tech Manufacturing Value Added (MHTMV)	A continuous variable. It represents the share of medium and high-tech manufacturing value added in total manufacturing value added and is expressed as a percentage	Ma et al. [47] Peng et al. [63]
Fixed Broadband Subscriptions (FBS)	A continuous variable expressing the number of fixed broadband subscriptions per 100 people	Czernich et al. [15]
Mobile Cellular Subscriptions (MCS)	A continuous variable expressing the number of mobile cellular subscriptions per 100 people	Wiranatakusuma and Zakaria [87] Musa et al. [53] Amaghionyeodiwe and Annansingh-Jamieson [4]

Source: Developed by Author, 2025

The primary objective of this research is to analyse the extent to which digitalisation influences economic growth and facilitates sustainability. Given that GDP per capita serves as a standardised and widely accepted indicator of economic development, this study evaluates sustainable economic advancement through its association with key ICT-related variables. Accordingly, an economic model is constructed to explore the relationship between digital integration and sustainable economic development, allowing for a comprehensive assessment of how digital technologies contribute to long-term economic progress.

$$GDP\_pc = f(IPR,\ ICT\_SE,\ \ ICT\_GI, CCS, MHTMV, FBS, MCS) \qquad (1)$$

The empirical formulation of the model is outlined as follows:

$$\mathrm{GDP\_pc}_t = \alpha_0 + \alpha_1 IPR_t + \alpha_2 \mathrm{ICT\_SE}_t + \alpha_3 \mathrm{ICT\_GI}_t + \alpha_4 CCS_t + \alpha_5 \mathrm{MHTMV}_t + \alpha_6 \mathrm{FBS}_t + \alpha_7 \mathrm{MCS}_t + u_t \qquad (2)$$

Herein,

$\mathrm{GDP\_pc_t}$ = Explained Variable; $\mathrm{IPR_t}, \mathrm{ICT\_SE_t}, \mathrm{ICT\_GI_t}, \mathrm{CCS_t}, \mathrm{MHTMV_t}, \mathrm{FBS_t}, \mathrm{MCS_t}$ = Explanatory Variables in the t Year; u_t = Unobservable (error term); $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6$ = Slope Parameters (elasticities).

3.1 Stationarity

To estimate effects accurately, the stationarity of the time series must first be tested. Optimal lag selection is a key challenge in unit root testing, extensively explored by researchers [1; 14; 48; 88]. Selection criteria include FPE, HQIC Hannan and Quinn [27], BIC Schwarz [75], and AIC [2]. A time series is stationary if its mean, variance, and autocorrelation remain constant over time. Common tests include the ADF, PP, KPSS, DF-GLS, and Zivot-AndrewsThe null and alternative hypotheses associated with the widely employed stationarity tests—specifically, the Augmented Dickey-Fuller (ADF) test [19] and the Phillips-Perron (PP) test [67]—which are grounded in the autoregressive model (2), are formulated as follows:

H_0: The process has a unit root; H_1: The process does not have a unit root.

In instances where time series variables are stationary, indicating the absence of a deterministic trend, analytical techniques such as Ordinary Least Squares (OLS) or Vector Autoregressive (VAR) models can be applied to yield consistent and unbiased parameter estimates. However, when all variables exhibit non-stationarity but are cointegrated—implying a stable long-term association—the appropriate methodological choice is the Vector Error Correction Model (VECM), which is grounded in the Johansen cointegration methodology [37]. For datasets comprising variables with differing integration orders, specifically where some variables are stationary at level (I(0)) and others achieve stationarity following first differencing (I(1)), the Autoregressive Distributed Lag (ARDL) model provides a robust alternative. Originally discussed in early econometric work [3] and later refined by Pesaran, Shin, and Smith [65; 66], the ARDL framework accommodates both short-term dynamics and long-term equilibrium relationships, irrespective of whether the explanatory variables are exclusively I(0), I(1), or a combination of both integration levels.

3.2 Cointegration Test

Cointegration analysis provides an essential econometric method for identifying possible long-term equilibrium relationships among non-stationary time series variables. The foundational concept was initially proposed by Granger [24] and later expanded through further theoretical advancements by [24]. Several testing methodologies have since been developed to examine cointegration, including the Engle–Granger Two-Step Test [21], the Johansen Cointegration Test [37], and the ARDL Bounds Testing Procedure [56; 65; 66]. The Engle–Granger approach is limited to analysing bivariate systems, whereas both the Johansen and ARDL frameworks are suitable for assessing multivariate relationships. The Johansen method is applicable only when all series are integrated of order one (I(1)), while the ARDL Bounds approach is more flexible, accommodating combinations of level stationary (I(0)) and first-difference stationary (I(1)) variables. In instances where cointegration is detected, it becomes necessary to estimate a VECM, based on the Johansen framework, to capture both the long-run equilibrium dynamics and short-run deviations. The inclusion of the Error Correction Term (ECT) enables interpretation of the adjustment speed with which short-term disequilibria converge towards long-run stability. The functional form of this relationship is represented as follows:

$\Delta\mathrm{GDP\_pc}_t = \alpha_0 + \sum_{i=1}^{m} \varphi_i \Delta\mathrm{GDP\_pc}_{t-i} + \sum_{j=0}^{m} \rho_{1j} \Delta IPR_{t-j} + \sum_{j=0}^{m} \rho_{2j} \Delta\mathrm{ICT\_SE}_{t-j} + \sum_{j=0}^{m} \rho_{3j} \Delta\mathrm{ICT\_GI}_{t-j} + \sum_{j=0}^{m} \rho_{4j} \Delta CCS_{t-j} + \sum_{j=0}^{m} \rho_{5j} \Delta\mathrm{MHTMV}_{t-j} + \sum_{j=0}^{m} \rho_{6j} \Delta\mathrm{FBS}_{t-j} + \sum_{j=0}^{m} \rho_{7j} \Delta\mathrm{MCS}_{t-j} + \vartheta ECM_{t-1} + u_t$ (3)

Herein, φ and ρ are the short-run dynamic coefficients of the model and ϑ is the speed of adjustment.

In the absence of cointegration, the relationship between variables can still be effectively examined using the ARDL framework, particularly through the Bounds Testing Approach. Accordingly, Equation (2) may be reformulated in the ARDL specification as follows:

$\mathrm{GDP\_pc}_t = \alpha_0 + \sum_{i=1}^{m} \beta_i \mathrm{GDP\_pc}_{t-i} + \sum_{j=0}^{m} \alpha_{1j} IPR_{t-j} + \sum_{j=0}^{m} \alpha_{2j} \mathrm{ICT\_SE}_{t-j} + \sum_{j=0}^{m} \alpha_{3j} \mathrm{ICT\_GI}_{t-j} + + \sum_{j=0}^{m} \alpha_{4j} CCS_{t-j} + \sum_{j=0}^{m} \alpha_{5j} \mathrm{MHTMV}_{t-j} + \sum_{j=0}^{m} \alpha_{6j} \mathrm{FBS}_{t-j} + \sum_{j=0}^{m} \alpha_{7j} \mathrm{MCS}_{t-j} + u_t$ (4)

Where α_0 is the intercept, m is the lag order, u_t is the error term.

$\mathrm{GDP\_pc}_t$ is dependent variable while $IPR_t, \mathrm{ICT\_SE}_t,\ \mathrm{ICT\_GI}_t,\ CCS_t,\ \mathrm{MHTMV}_t,\ \mathrm{FBS}_t, \mathrm{MCS}_t$ are independent (explanatory) variables, α_{vj}, ($v = \overline{1,t}$ express the coefficients of explanatory variables, $j = \overline{0,m}$) and β_i, ($i = \overline{1,m}$) are the coefficients (elasticities), m is the lag order.

3.3 Supervised Machine Learning Models

Econometric techniques are essential for estimating variable influences and enabling meaningful economic interpretations. However, attaining high predictive accuracy increasingly necessitates the integration of machine learning (ML) methodologies. Within the domain of supervised learning, regression analysis serves a critical role by forecasting continuous target variables based on one or more explanatory features. Among the most frequently utilised models for time series forecasting are Random Forest, XGBRegressor, Long Short-Term Memory (LSTM) neural networks, ARIMA, and Support Vector Regression (SVR), as evidenced by numerous studies [23; 35; 57; 61; 62; 78]. ARIMA is particularly effective for capturing linear patterns and autocorrelation within stationary time series data, while also accommodating non-stationarity through differencing techniques. Its strength lies in its interpretability, which enhances its relevance for economic modelling and policy analysis. This model is especially advantageous when historical data trends are instrumental in forecasting future outcomes [13]. ARIMA has been extensively applied in both empirical and theoretical research settings [11; 20; 85; 86; 89].

In contrast, XGBRegressor is particularly suited to multivariate forecasting tasks and is capable of capturing non-linear interactions by identifying complex dependencies within datasets. Its growing significance in both applied and theoretical contexts is reflected across a wide range of recent studies [42; 55; 79; 91]. Based on the specific characteristics of the dataset under analysis, including stationarity and structural complexity, this research employs both ARIMA and XGBRegressor models. The general mathematical representations for these models are presented in Equations (5) and (6), respectively.

$\widehat{\mathrm{GDP\_pc}}_t = \sum_{k=1}^{K} f_k(IPR_t, \mathrm{ICT\_SE}_t, \mathrm{ICT\_GI}_t, CCS_t, \mathrm{MHTMV}_t, \mathrm{FBS}_t, \mathrm{MCS}_t)$ (5)

Where,

$\widehat{\mathrm{GDP\_pc}}_t$ is the predicted value of $\mathrm{GDP\_pc}_t$ at time t.

In this model, K denotes the total number of decision trees utilised. The learning process involves the sequential construction of these trees, where each successive tree is trained to reduce the residual errors of its predecessors. This is achieved through the gradient boosting method, which incrementally refines the model's predictive accuracy over successive iterations.

$\mathrm{GDP\_pc}_t = \mu + \sum_{i=1}^{p} \phi_i \mathrm{GDP\_pc}_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$ (6)

Where,

$\mathrm{GDP\_pc}_t$ is the value of the time series at time t
μ is the constant (drift) term.
ϕ_i are the autoregressive (AR) parameters for lag i (up to p).
θ_j are the moving average (MA) parameters for lag j (up to q).
ϵ_t is the error term (white noise at time t).
p and q are the number of autoregressive and moving average terms, respectively.

3.4 Data

As the study aims to assess how digitalisation contributes to sustainable development in Azerbaijan and Hungary, dedicated databases have been constructed for both countries. The analysis employs time series data from 2000 to 2023 (24 observations), focusing on core economic and digitalisation indicators: GDP per capita, Internet Penetration Rate, ICT Service Exports, ICT Goods Imports, Computer, Communications and Other Services, Medium and High-Tech Manufacturing Value Added, Fixed Broadband Subscriptions, and Mobile Cellular Subscriptions. The data have been sourced from secondary materials, including the Statistical Committee of the Republic of Azerbaijan, the Hungarian Central Statistical Office, Statista, and Trading Economics.

4. Empirical Analysis and Discussion

This study adopts a combined methodological approach, employing both descriptive and analytical techniques by integrating conventional econometric models with contemporary machine learning algorithms to ensure reliable economic forecasting. The analytical process involves the following sequential steps.

4.1 Statistical Analysis of Variables

A thorough examination of the fundamental characteristics of key economic variables—such as their distributional properties, interrelationships, and temporal trends—is a critical preliminary step in empirical research. This process facilitates pattern recognition and informs the modelling strategy. In recognition of this significance, the study applies descriptive statistical methods, correlation analysis, and data visualisation tools to explore the initial dynamics of the dataset. The summary statistics for the core indicators used in the analysis for both Azerbaijan and Hungary are presented in Table 2.

Table 2
Descriptive Statistics

	GDP_PER_CAP	FBS	CCS	ICT_GI	ICT_SE	IPR	MCS	MHTMV
Azerbaijan								
Mean	4473.363	10.20625	28.00000	4.377917	3.083333	46.88333	74.64125	11.00000
Median	4824.300	12.56500	27.50000	3.950000	2.600000	52.10000	101.3000	10.00000
Maximum	7990.800	20.88000	48.00000	8.970000	6.800000	88.00000	108.0000	18.00000
Minimum	662.9000	0.000000	12.00000	2.400000	0.300000	0.000000	5.000000	6.000000
Std. Dev.	2525.454	9.254744	11.18617	1.600587	1.784637	35.33245	40.59191	2.978182
Jarque-Bera	1.571638	3.533202	1.511686	12.15591	1.666609	3.008103	3.701514	4.258701
Probability	0.455746	0.170913	0.469614	0.002293	0.434611	0.222228	0.157118	0.118914
Hungary								
Mean	12364.58	20.51167	48.83333	16.67917	7.633333	60.12500	100.6125	52.95833
Median	11750.00	23.70500	50.00000	17.50000	8.100000	69.50000	104.5000	52.50000
Maximum	16300.00	36.79000	60.00000	21.20000	12.70000	91.00000	141.7000	59.00000
Minimum	8970.000	0.030000	37.00000	10.00000	2.500000	7.000000	30.00000	46.00000
Std. Dev.	2072.199	12.46330	4.650074	3.591654	2.640103	25.70115	24.33363	3.507497
Jarque-Bera	1.242651	2.159615	3.076963	2.225942	0.509780	2.875204	10.06944	0.254642
Probability	0.537232	0.339661	0.214707	0.328581	0.775002	0.237497	0.006508	0.880451

Source: Author's Calculation, 2025

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The descriptive evaluation of major economic variables reveals notable contrasts in the levels of economic performance and digital advancement between Azerbaijan and Hungary. Hungary demonstrates comparatively higher levels of development across all key indicators, including GDP per capita, ICT trade (covering both the import of ICT goods and the export of ICT services), fixed broadband penetration, and the share of high-technology manufacturing. In contrast, Azerbaijan exhibits greater variability in certain metrics and lags particularly in mobile penetration and ICT service exports. Normality of the data was assessed using the Jarque–Bera test. The findings indicate that most variables adhere to the assumption of normal distribution, with the exception of ICT Goods Imports (ICT_GI) in Azerbaijan and Mobile Cellular Subscriptions (MCS) in Hungary, both of which deviate from normality at the 5% significance level. To assess the potential presence of multicollinearity, a correlation matrix (Figure 1) was initially analysed, followed by the computation of the Variance Inflation Factor (VIF), as reported in Table 3.

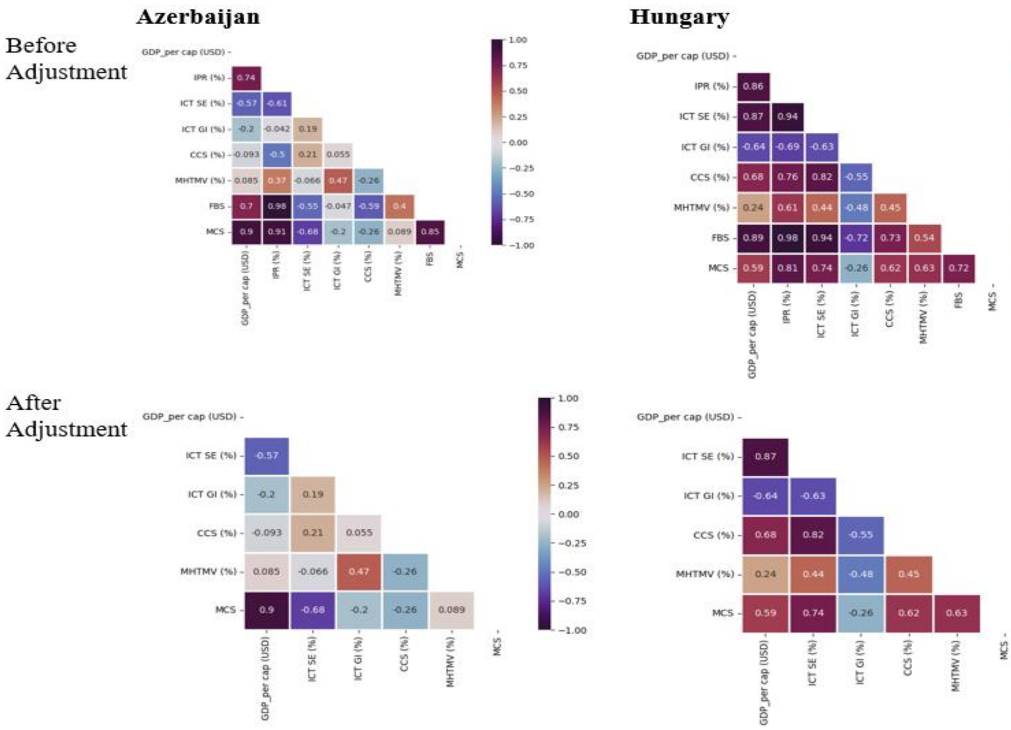

Fig. 1: Correlation Analysis Heatmap
Source: Developed by the Author using Python

Based on the correlation and VIF results, variables exhibiting high interdependence were removed from the model. Following these adjustments, multicollinearity was effectively mitigated, as evidenced by the final VIF diagnostics summarised in Table 3.

Table 3
VIF Results

Azerbaijan				**Hungary**			
Before Adjustment		After Adjustment		Before Adjustment		After Adjustment	
Variable	VIF	Variable	VIF	Variable	VIF	Variable	VIF
GDP_PER_CAP	12.36	GDP_PER_CAP	5.95	GDP_PER_CAP	9.63	GDP_PER_CAP	5.77
ICT_SE	2.09	ICT_SE	1.91	ICT_SE	17.31	ICT_SE	9.13
ICT_GI	1.52	ICT_GI	1.05	ICT_GI	5.38	ICT_GI	4.21
CCS	2.88	CCS	1.20	CCS	3.67	CCS	3.10
MCS	76.13	MCS	7.68	MCS	15.28	MCS	5.97
FBS	63.62	MHTMV	1.52	FBS	108.26	MHTMV	3.72
IPR	145.50			IPR	188.84		
MHTMV	4.07			MHTMV	5.05		

Source: Author's Calculation, 2025

4.2 Testing Stationarity

Lag selection plays a pivotal role in time series modelling, as it determines the extent to which historical values influence the current and future behaviour of a variable. The accuracy and stability of econometric models are highly dependent on identifying the optimal lag structure, particularly in analyses involving unit root testing, cointegration assessments, and Vector Autoregression (VAR) modelling [27; 30; 33; 45]. In light of this, the optimal lag length was determined prior to performing stationarity tests. Both one and two lag structures were assessed, and using selection criteria including the Akaike Information Criterion (AIC), Final Prediction Error (FPE), Hannan–Quinn Criterion (HQ), and Likelihood Ratio (LR) test results, the appropriate lag length was identified as two for both Azerbaijan and Hungary (Table 4).

Table 4
VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
Hungary						
0	-461.3695	NA	1.14e+11	42.48814	42.78569	42.55823
1	-357.4685	141.6831	2.73e+08	36.31532	38.39822	36.80599
2	-287.1487	57.53443*	30277198*	33.19534*	37.06358*	34.10658*
Azerbaijan						
0	-498.1457	NA	3.23e+12	45.83143	46.12898	45.90152
1	-397.5631	137.1581	1.05e+10	39.96028	42.04318	40.45095
2	-323.6718	60.45651*	8.38e+08*	36.51562*	40.38386*	37.42686*

* Indicates lag order designated by the criterion
Endogenous variables: GDP_PER_CAP, ICT_SE, ICT_GI, MHTMV, MCS, CCS; Included observations: 22
Source: Author's Calculation, 2025

The outcomes of the ADF test indicate that GDP per capita, ICT_SE, ICT_GI, and MHTMV are non-stationary in their level forms but become stationary following first differencing, identifying them as I(1) variables (Table 5). The variable CCS is nearly stationary at level and attains full stationarity after first differencing. In the case of MCS, second differencing was applied for both Azerbaijan and Hungary. The resulting p-values under constant (C) and constant with trend (C&T) specifications—0.0014 and 0.0002 for C, and 0.002 and 0.0013 for C&T—are all below the 5 percent significance threshold, confirming that MCS is integrated of order two (I(2)).

Given the mixed order of integration across the dataset, where MCS is I(2) while the other variables are I(0) or I(1), a VECM is deemed the most appropriate modelling framework for capturing both the long-term equilibrium relationships and short-run dynamics.

Table 5
Augmented Dickey-Fuller (ADF) Unit Root Test Results

Hungary					
Variables		**Level**		**1st level**	
		C	**C&T**	**C**	**C&T**
GDP_per	T-Statistic	0.017271	-1.310518	-4.406175	-4.355016
cap (USD)	P-Value	0.9510	0.8593	0.0024	0.0119
ICT SE (%)	T-Statistic	-1.892851	-2.095786	-4.580715	-4.728198
	P-Value	0.3295	0.5210	0.0016	0.0055
ICT GI (%)	T-Statistic	-1.934366	-2.164207	-4.321944	-4.127996
	P-Value	0.3117	0.4857	0.0029	0.0189
CCS (%)	T-Statistic	-3.155816	-5.064443	-5.236153	-5.252499
	P-Value	0.0363	0.0027	0.0004	0.0020
MCS	T-Statistic	-2.984295	-2.781314	-2.475518	-1.714655
	P-Value	0.0514	0.2172	0.1345	0.7101
MHTMV	T-Statistic	-1.737978	-1.302294	-4.721168	-5.259638
	P-Value	0.4000	0.8615	0.0012	0.0018

Table 5 (cont…)
Augmented Dickey-Fuller (ADF) Unit Root Test Results

Azerbaijan					
GDP_per	T-Statistic	-1.815565	--1.963123	-3.286939	-3.233110
cap (USD)	P-Value	0.3635	0.5883	0.0282	0.1039
ICT SE (%)	T-Statistic	-2.410727	0.1503	-4.117447	-4.224677
	P-Value	-3.206329	0.1088	0.0052	0.0171
ICT GI (%)	T-Statistic	-0.437095	-0.610205	-3.091739	-4.701120
	P-Value	0.8853	0.9672	0.0435	0.0062
CCS (%)	T-Statistic	-1.591829	-1.812488	-4.181884	-4.104043
	P-Value	0.4705	0.6655	0.0040	0.0199
MCS	T-Statistic	-1.923279	-1.412021	-1.765590	-2.199077
	P-Value	0.3162	0.8282	0.3865	0.4669
MHTMV	T-Statistic	-0.810460	-1.309076	-5.025035	-5.711922
	P-Value	0.7972	0.8597	0.0006	0.0007

Source: Author's Calculation, 2025

4.3 Johansen's Test to Cointegration

The Johansen test is employed to evaluate whether a long-run equilibrium association exists among non-stationary time series variables. The findings of this study confirm the presence of cointegration up to rank 4 for both Azerbaijan and Hungary (Table 6). In light of these results, the use of a VECM is warranted for both countries, as the existence of cointegration justifies its application. The VECM framework is particularly suited to datasets exhibiting long-term equilibrium relationships, as it enables the simultaneous modelling of both long-run associations and short-term adjustments.

Table 6
Johansen Cointegration Test Result

Countries/ ranks	Azerbaijan		Hungary	
None	Trace Statistic	186.53	Trace Statistic	195.05
	Critical Value (5%)	95.75	Critical Value (5%)	95.75
At Most 1	Trace Statistic	117.96	Trace Statistic	115.35
	Critical Value (5%)	69.82	Critical Value (5%)	69.82
At Most 2	Trace Statistic	71.37	Trace Statistic	52.38
	Critical Value (5%)	47.86	Critical Value (5%)	47.86
At Most 3	Trace Statistic	35.3	Trace Statistic	30.22
	Critical Value (5%)	29.80	Critical Value (5%)	29.79
At Most 4	Trace Statistic	15.8	Trace Statistic	13.07
	Critical Value (5%)	15.49	Critical Value (5%)	15.49
At Most 5	Trace Statistic	0.95	Trace Statistic	1.74
	Critical Value (5%)	3.84	Critical Value (5%)	3.84

Source: Author's Calculation, 2025

4.4 Estimate the VECM Model

The VECM is employed to estimate both the short-term dynamics and long-term equilibrium relationships between GDP per capita and its associated explanatory variables. The estimation results reveal three distinct cointegrating vectors (CointEq1, CointEq2, and CointEq3), indicating the existence of stable long-run associations among the variables under investigation for both Azerbaijan and Hungary (Table 7).

Table 7
VECM Results

Variable	CointEq1		CointEq2		CointEq3		Short-Run Dynamics	
	AZ	HUN	AZ	HUN	AZ	HUN	AZ	HUN
GDP_PER_CAP (-1)	1.000	1.000	0.000	0.000	0.000	0.000	0.192	0.066
							[0.86]	[0.14]
ICT_GI (-1)	0.000	0.000	1.000	1.000	0.000	0.000	-130.62	-25.69
							[-0.61]	[-0.39]
ICT_SE (-1)	0.000	0.000	0.000	0.000	1.000	1.000	146.37	23.715
							[0.78]	[0.17]
MCS(-1)	-77.77	-12.74	0.057	-0.325	0.025	0.039	-71.061	18.634
	[-19.86]*	[-1.41]	[6.61]*	[-4.33]*	[6.98]*	[1.51]	[-1.58]	[1.056]
MHTMV (-1)	-56.79	-31.887	-0.551	1.796	0.105	-0.295	57.488	-73.032
	[-0.67]	[-0.71]	[-2.96]*	[4.83]*	[1.35]	[2.34]*	[0.49]	[-1.53]
CCS (-1)	-173.68	-516.28	0.101	1.540	-0.079	-0.871	-23.209	-4.532
	[-8.21]*	[-14.82]*	[2.14]*	[5.32]*	[-3.99]*	[-8.86]*	[-0.61]	[-0.092]
C	6924.23	16118.01	-5.35	-154.8	-3.83	46.95	547.171	225.84
							[1.93]	[1.078]
Error Correction Terms (CointEq1, CointEq2, CointEq3)	-0.524 [-2.43]	-0.002 [-0.013]	-147.7 [-1.30]	87.767 [1.55]	-365.5 [-1.84]	66.990 [0.44]		

Note: * indicates significance at 1%,
Source: Author's Calculation, 2025

The VECM results show that CCS and MCS exert significant negative long-run effects on GDP per capita in both countries, while other variables display insignificant impacts. Co-integration relationships are visualised in Figure 2a and Figure 2b.

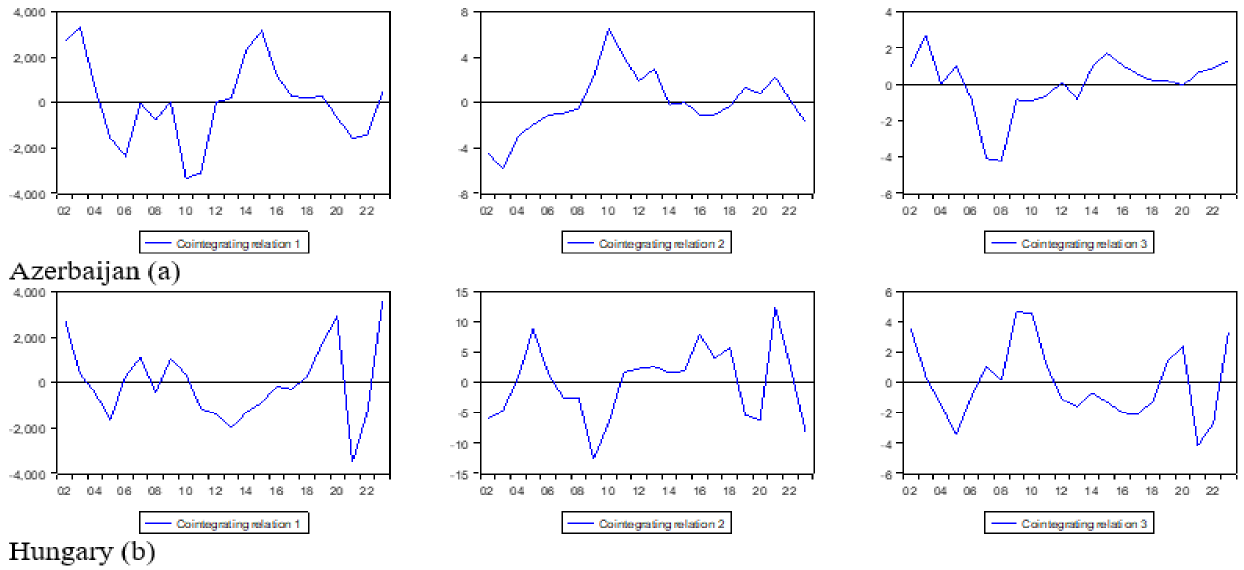

Fig. 2: (a, b) Co-integration Graph for Azerbaijan and Hungary
Source: Developed by the Author using E-Views

In the short term, ICT variables largely lack statistical significance, though MCS(-1) in Azerbaijan and CCS(-1) in Hungary have notable negative effects. The ECT indicates faster adjustment in Azerbaijan (-0.524, t = -2.43) compared to Hungary (-0.002, t = -0.013). IRF plots (Figures 3 and 4) reveal smoother long-run adjustment for Hungary, while Azerbaijan experiences greater volatility and sensitivity to external shocks.

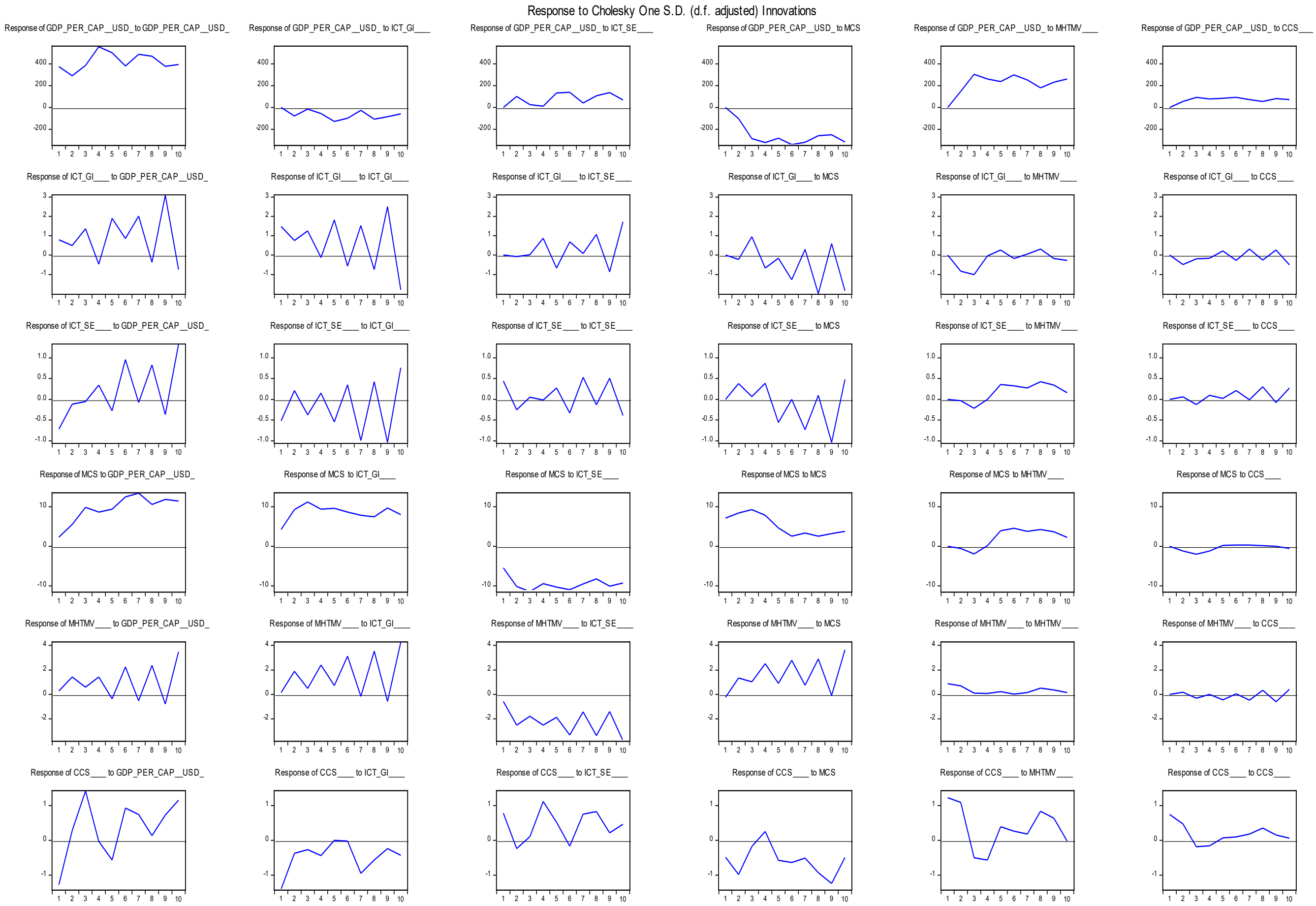

Fig.3: Impulse Response Graph (For Hungary)
Source: Developed by the Author using E-Views

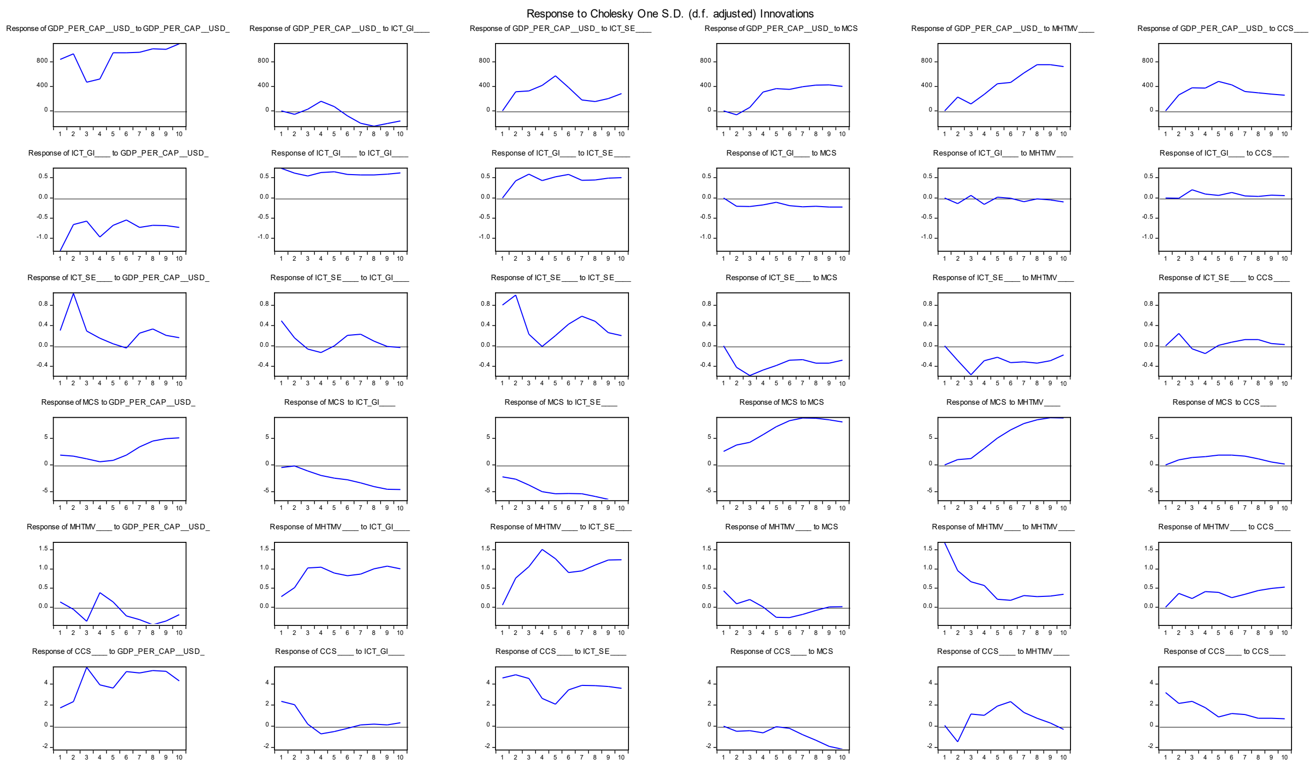

Fig.4: Impulse Response Graph (For Azerbaijan)
Source: Developed by the Author using E-Views

The VECM model explains 64.83 percent of the variation in GDP per capita for Azerbaijan and 58.41 percent for Hungary, indicating a slightly better model fit in the case of Azerbaijan based on the R^2 value. Despite this, Hungary records a notably lower Sum of Squared Residuals (SSR), at 372.15 compared to 842.48 for Azerbaijan, suggesting greater predictive accuracy. Furthermore, although Azerbaijan's model yields a higher F-statistic, indicating marginally stronger overall model significance, the values remain below the commonly accepted threshold of 4–5 for robust statistical relevance (Table 8).

Table 8
Goodness-of-Fit

Metrics/Countries (D(GDP_PER_CAP__USD_))	Azerbaijan	Hungary
R-Squared	0.648348	0.584076
Adj. R-Squared	0.384609	0.272133
Sum sq. resids	8517343.	1661921.
S.E. Equation	842.4836	372.1470
F-Statistic	2.458293	1.872380

Source: Author's Calculation, 2025

Moreover, diagnostic analysis results (Table 9) show no autocorrelation (LM test), normally distributed residuals (Jarque-Bera test), and constant variance (ARCH test), confirming model reliability.

Table 9
Diagnostic Analysis

Metrics/countries		Azerbaijan	Hungary
LM Test		Prob. 0.6550/ 0.8865	Prob. 0.2531/ 0.6253
Jarque-Bera Test	Chi-sq	4.794292	16.8837
	p-value	0.9645	0.1540
ARCH Test	Chi-sq	396.0000	396.0000
	p-value	0.2518	0.2518

Source: Author's Calculation, 2025

4.5 Prediction via Machine Learning Models

To improve predictive performance, the study also incorporated supervised machine learning techniques alongside conventional econometric approaches. In particular, ARIMA and XGBRegressor models were employed to generate forward-looking estimates. The five-year forecasts covering the period from 2024 to 2028 for both Azerbaijan and Hungary are summarised in Table 10 and illustrated in Figure 5a and Figure 5b.

Table 10
Future Prediction using ARIMA and XGBRegressor

Years /countries	Azerbaijan		Hungary	
	ARIMA	XGBRegressor	ARIMA	XGBRegressor
2024	6242.10	$7347.86	$16607.21	$14263.79
2025	6359.16	$7392.60	$16914.42	$14024.86
2026	6343.66	$7554.03	$17221.62	$14024.86
2027	6345.71	$7749.35	$17528.81	$14024.86
2028	6345.44	$7749.35	$17835.99	$14024.86

Source: Author's Calculation, 2025

The outcomes from both models offer notable insights. While XGBRegressor projects higher future values for Azerbaijan, ARIMA generates more comprehensive forecasts for GDP per capita, as depicted in Figure 5. Based on the evaluation metrics, specifically MAE and RMSE, ARIMA demonstrates superior predictive accuracy and reliability compared to XGBRegressor (Table 11).

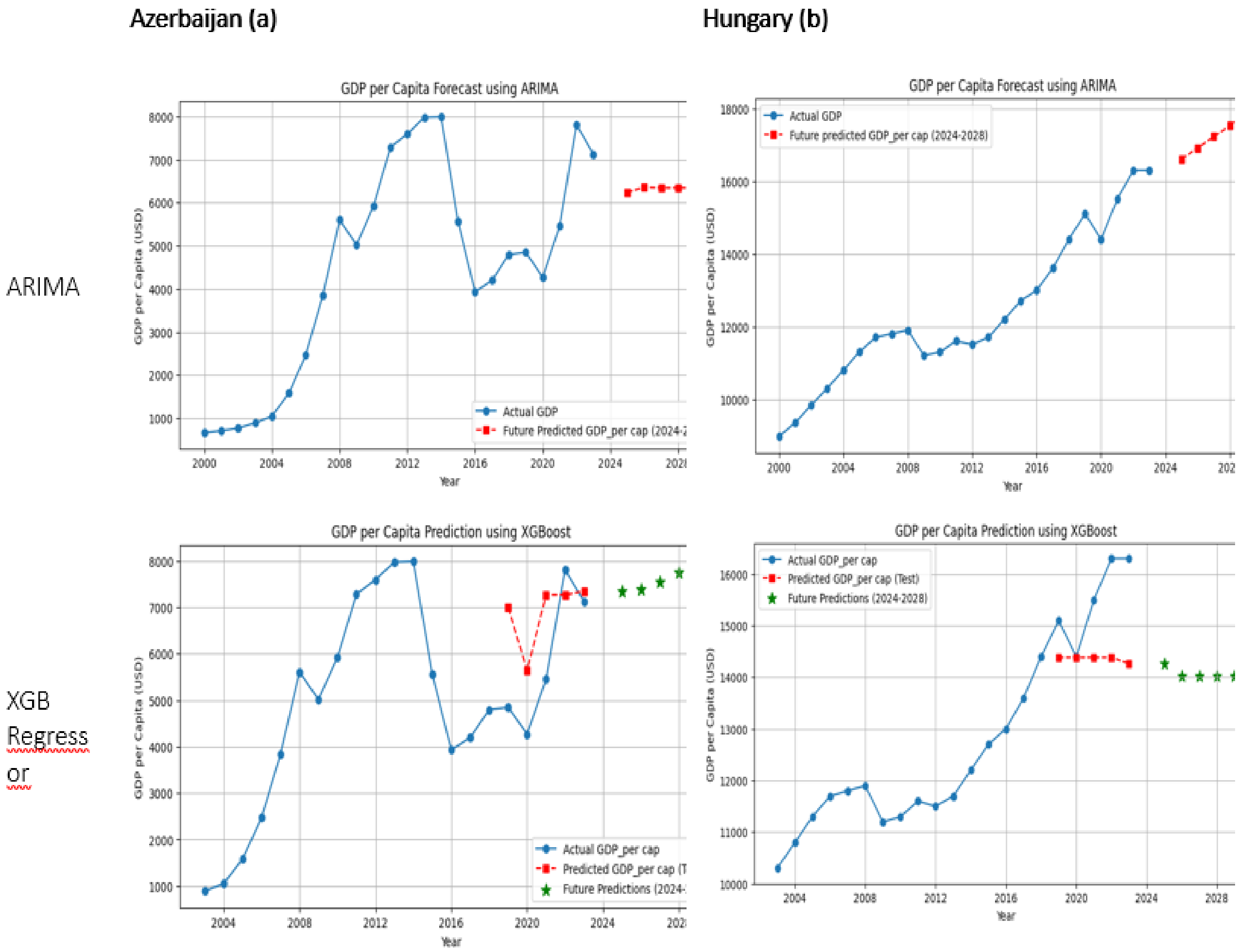

Fig. 5 (a, b): 5 Years' Future Prediction for Azerbaijan and Hungary
Source: Developed by the Author using Python

Table 11
Performance Metrics

	Azerbaijan		Hungary	
	ARIMA	XGBRegressor	ARIMA	XGBRegressor
Mean Absolute Error (MAE)	695.43	1219.10	326.16	1159.02
Root Mean Squared Error (RMSE)	937.19	14.24.39	429.15	1383.18

Source: Author's Calculation, 2025

5. Discussion

This study investigates the link between digitalisation and economic sustainability by drawing a comparative analysis of two developing nations, Azerbaijan and Hungary. Although both countries fall within the developing category, they exhibit considerable disparities in macroeconomic performance and ICT advancement. Hungary demonstrates a significantly higher GDP per capita, suggesting a more mature economic structure, whereas Azerbaijan's income levels display greater volatility over time, indicative of heightened economic fluctuations (Table 2). Hungary's ICT infrastructure is also considerably more advanced. The volume of ICT goods imports and service exports is substantially higher, underscoring Hungary's more established role in international digital trade. Conversely, Azerbaijan's lower ICT service export figures reflect a comparatively nascent digital services sector. These discrepancies can be attributed to differences in economic orientation, public policy priorities, investment capacity in digital systems, and human capital development. Hungary's membership in the European Union has provided broader access to external funding and global markets, accelerating ICT development. In contrast, Azerbaijan remains in an expansion phase, with national strategies geared towards modernising its digital landscape and improving connectivity.

These divergences in ICT maturity inevitably affect GDP per capita, as a robust digital sector tends to enhance productivity, innovation, and international competitiveness [5; 26; 29; 81]. The impact of ICT services on GDP per capita has been widely explored across various economies, with mixed conclusions. Some studies report a positive and statistically significant relationship, while others suggest negative outcomes and advocate for improvements in digital infrastructure [6; 44; 69; 88]. Mobile connectivity's role in economic performance has also drawn scholarly interest, with the majority of studies confirming a positive impact [4; 53; 87]. However, our findings indicate that MCS exerts a negative influence on economic growth in both countries. Possible explanations include low-value usage, limited digital literacy, underutilised infrastructure, and inefficiencies within the telecommunications sector. In response, the next phase of this research will assess digital literacy levels in Azerbaijan and Hungary.

The results also show that MHTMV has a negative but statistically insignificant effect on GDP per capita in both contexts. This may be attributed to underdeveloped high-tech manufacturing sectors and broader structural constraints [47; 63]. While previous research has linked CCS exports to economic advancement [44; 52], this study finds a negative effect in both nations. The result may stem from structural challenges, including a lack of service diversity, inadequate infrastructure, and weak integration into global digital value chains. Azerbaijan has made notable progress in ICT development due to strategic reforms and state-led initiatives. Policies such as the "Azerbaijan 2030: National Priorities for Socio-Economic Development", the State Programme on the Expansion of Digitalisation and Innovation, and various projects spearheaded by the Ministry of Digital Development and Transport have fostered this growth. Key reforms include the E-Government platform aimed at enhancing digital public service delivery, the National Broadband Internet Project to improve internet access, and efforts to support ICT entrepreneurship and foreign direct investment in technology. Collectively, these initiatives have significantly strengthened Azerbaijan's digital economy and supported innovation-led growth [70].

6. Conclusion

This study assessed the influence of digitalisation on sustainable economic development in Azerbaijan and Hungary by integrating traditional econometric analysis (VECM) with supervised machine learning techniques (ARIMA and XGBRegressor) to ensure both interpretive robustness and predictive accuracy. The short-term estimations revealed mixed and statistically insignificant effects. In Azerbaijan, a 1% reduction in ICT_GI as a share of total imports corresponded with a \$130.62 rise in GDP per capita, whereas a 1% increase in ICT_SE resulted in a \$148.70 decline. An alternative estimation suggested that a similar increase in ICT_SE could raise GDP per capita by \$23.715. Furthermore, a 1% growth in CCS was associated with GDP per capita declines of \$23.209 in Azerbaijan and \$4.532 in Hungary. Despite these observed fluctuations, none of the short-run impacts achieved statistical significance, indicating that digitalisation may not yield immediate economic returns and that its benefits could take time to materialise. In contrast, the long-term findings presented stronger and more conclusive results. An increase of 1% in CCS led to reductions in GDP per capita by \$173.68 in Azerbaijan and \$516.28 in Hungary. Additionally, each additional mobile subscription per 100 individuals resulted in a \$77.77 decline in GDP per capita in Azerbaijan. Similarly, a 1% increase in MHTMV reduced GDP per capita by \$56.79 over the long term, indicating structural inefficiencies or underutilised digital capacities. To complement these insights and improve forecast accuracy, both ARIMA and XGBRegressor were employed. ARIMA demonstrated superior performance in terms of predictive reliability. The forecasts suggest a positive economic trajectory for Hungary, while Azerbaijan is likely to face economic contraction over the forthcoming five-year period. These results align with the broader econometric evidence, which illustrates greater volatility and instability in Azerbaijan's economic indicators compared to Hungary.

Recommendation

Drawing from the results of this study, the following policy recommendations are proposed to strengthen the economic contribution of digitalisation in Azerbaijan and Hungary:

For Azerbaijan

i. Enhance the global competitiveness of ICT service exports by fostering innovation ecosystems, introducing targeted fiscal incentives, and attracting international capital.

ii. Strengthen e-governance systems to address inefficiencies and expand the accessibility and quality of digital public services.

iii. Increase strategic investments in ICT infrastructure, particularly in sectors associated with high-value-added services and technological innovation, to generate long-term economic gains.

For Hungary

Utilise the advantages of European Union digital policy frameworks to accelerate Industry 4.0 implementation. Emphasis should be placed on encouraging smart technology integration in manufacturing and services, improving regional ICT trade flows, and expanding international digital cooperation to maintain economic momentum.

For Both Countries

Develop and implement comprehensive national digital strategies that prioritise sustained investment in digital transformation. This should be accompanied by initiatives aimed at improving digital literacy and establishing transparent regulatory frameworks to ensure that digitalisation translates into meaningful economic growth.

Future research will explore the measurement of digital literacy and assess its influence on the digital economy in both national contexts. The successful implementation of these strategic measures could enable Azerbaijan and Hungary to strengthen the economic returns of digitalisation, foster inclusive and sustainable development, and build resilience against future economic disruptions.

References

[1] Agunloye, O. K., Arnab, R., & Shangodoyin, D. K. (2013). A new criterion for lag-length selection in unit root tests. *American Journal of Theoretical and Applied Statistics*, *2*(6), 293-298. http://doi.org/10.11648/j.ajtas.20130206.28

[2] Akaike, H. (1969). Fitting autoregreesive models for prediction. In *Selected Papers of Hirotugu Akaike* (pp. 131-135). Springer. https://doi.org/10.1007/978-1-4612-1694-0_10

[3] Almon, S. (1965). The distributed lag between capital appropriations and expenditures. *Econometrica: Journal of the Econometric Society*, 178-196. https://doi.org/10.2307/1911894

[4] Amaghionyeodiwe, L. A., & Annansingh-Jamieson, F. (2017). An investigation into the impact of mobile technologies on economic growth and employment in the Caribbean. *Athens journal of business & economics*, *3*(3), 263-277. http://hdl.handle.net/11159/894

[5] Aranyossy, M., Nemeslaki, A., & Fekó, A. (2014). Empirical Analyis of Public ICT Development Project Objectives in Hungary. *International Journal of Advanced Computer Science and Applications*, *5*(12). https://pdfs.semanticscholar.org/4b3c/5157398f5a48c0dc2351e6627fa1ad7aaaf1.pdf

[6] Bahrini, R., & Qaffas, A. A. (2019). Impact of information and communication technology on economic growth: Evidence from developing countries. *Economies*, *7*(1), 21. https://doi.org/10.3390/economies7010021
[7] Bank, A. D. (2024). Asian Development Outlook. 22: Asian Development Bank. https://dx.doi.org/10.22617/FLS240598-3
[8] Barbier, E. (2011). The policy challenges for green economy and sustainable economic development. Natural resources forum, 233-245. https://doi.org/10.1111/j.1477-8947.2011.01397.x
[9] Barbier, E. B. (2016). Is green growth relevant for poor economies? *Resource and energy economics*, *45*, 178-191. https://doi.org/10.1016/j.reseneeco.2016.05.001
[10] Barrier, E. B. (2017). The concept of sustainable economic development. In *The economics of sustainability* (pp. 87-96). Routledge. https://doi.org/10.4324/9781315240084
[11] Benvenuto, D., Giovanetti, M., Vassallo, L., Angeletti, S., & Ciccozzi, M. (2020). Application of the ARIMA model on the COVID-2019 epidemic dataset. *Data in brief*, *29*, 105340. https://doi.org/10.1016/j.dib.2020.105340
[12] Bhutani, S., & Paliwal, Y. (2015). Digitalization: A step towards sustainable development. *OIDA International Journal of Sustainable Development*, *8*(12), 11-24. https://ssrn.com/abstract=2713132
[13] Box, G., & Jenkins, G. (1976). Analysis: Forecasting and Control. *San francisco*. https://www.scirp.org/reference/referencespapers?referenceid=2087370
[14] Cavaliere, G., Rahbek, A., & Robert Taylor, A. (2014). Bootstrap determination of the co-integration rank in heteroskedastic VAR models. *Econometric Reviews*, *33*(5-6), 606-650. https://doi.org/10.1080/07474938.2013.825175
[15] Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal*, *121*(552), 505-532. https://doi.org/10.1111/j.1468-0297.2011.02420.x
[16] Dedrick, J., Kraemer, K. L., & Shih, E. (2013). Information technology and productivity in developed and developing countries. *Journal of Management Information Systems*, *30*(1), 97-122. https://doi.org/10.2753/MIS0742-1222300103
[17] Development, A. D. (2023). *Azerbaijan Digital Development: facts and figures.* . https://mincom.gov.az/storage/Statistika-kitab-ENG.pdf
[18] Diaz-Rainey, I., & Ashton, J. K. (2015). Investment inefficiency and the adoption of eco-innovations: The case of household energy efficiency technologies. *Energy Policy*, *82*, 105-117. https://doi.org/10.1016/j.enpol.2015.03.003
[19] Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: Journal of the Econometric Society*, 1057-1072. https://doi.org/10.2307/1912517
[20] Dubey, A. K., Kumar, A., García-Díaz, V., Sharma, A. K., & Kanhaiya, K. (2021). Study and analysis of SARIMA and LSTM in forecasting time series data. *Sustainable Energy Technologies and Assessments*, *47*, 101474. https://doi.org/10.1016/j.seta.2021.101474
[21] Engle, R. F., & Yoo, B. S. (1987). Forecasting and testing in co-integrated systems. *Journal of Econometrics*, *35*(1) 143-159. https://doi.org/10.1016/0304-4076(87)90085-6
[22] Geels, F. W. (2005). Technological transitions and system innovations: a co-evolutionary and socio-technical analysis. In *Technological transitions and system innovations*. Edward Elgar Publishing. https://doi.org/10.4337/9781845424596
[23] Gogas, P., & Papadimitriou, T. (2021). Machine learning in economics and finance. *Computational Economics*, *57*(1), 1-4. https://doi.org/10.1007/s10614-021-10094-w

[24] Granger, C. W. (1983). *Co-integrated variables and error-correcting models* Discussion Paper 83-13. Department of Economics, University of California at ...]. https://www.scirp.org/reference/referencespapers?referenceid=2415681

[25] Gupta, S., & Rhyner, J. (2022). Mindful application of digitalization for sustainable development: The Digitainability Assessment Framework. *Sustainability*, *14*(5), 3114. https://doi.org/10.3390/su14053114

[26] Guseynov, S., Abdullaev, R., Mehdiyev, T., & Edelkina, A. (2021). Information & communication technologies (ICT) and economic development of the Azerbaijan Republic. *Journal of World economy: Transformations & transitions*, *1*(1), 1. https://dialnet.unirioja.es/servlet/articulo?codigo=8023722

[27] Hannan, E. J., & Quinn, B. G. (1979). The determination of the order of an autoregression. *Journal of the Royal Statistical Society: Series B (Methodological)*, *41*(2), 190-195. https://doi.org/10.1111/j.2517-6161.1979.tb01072.x

[28] Harb, G. (2017). The economic impact of the Internet penetration rate and telecom investments in Arab and Middle Eastern countries. *Economic analysis and policy*, *56*, 148-162. https://doi.org/10.1016/j.eap.2017.08.009

[29] Harindranath, G. (2008). ICT in a transition economy: The case of Hungary. *Journal of Global Information Technology Management*, *11*(4), 33-55. https://doi.org/10.1080/1097198X.2008.10856478

[30] Hassani, H., & Yeganegi, M. R. (2020). Selecting optimal lag order in Ljung–Box test. *Physica A: Statistical Mechanics and its Applications*, *541*, 123700. https://doi.org/10.1016/j.physa.2019.123700

[31] Irajifar, L., Chen, H., Lak, A., Sharifi, A., & Cheshmehzangi, A. (2023). The nexus between digitalization and sustainability: A scientometrics analysis. *Heliyon*, *9*(5). https://doi.org/10.1016/j.heliyon.2023.e15172

[32] ITU. (2024). *Measuring digital development: Facts and Figures*. https://www.itu.int/en/ITU-D/Statistics/pages/facts/default.aspx

[33] Ivanov, V., & Kilian, L. (2005). A practitioner's guide to lag order selection for VAR impulse response analysis. *Studies in Nonlinear Dynamics & Econometrics*, *9*(1). https://doi.org/10.2202/1558-3708.1219

[34] Jia, W., Collins, A., & Liu, W. (2023). Digitalization and economic growth in the new classical and new structural economics perspectives. *Digital Economy and Sustainable Development*, *1*(1), 5. https://doi.org/10.1007/s44265-023-00007-0

[35] Jiang, Z. (2022). Prediction and industrial structure analysis of local GDP economy based on machine learning. *Mathematical Problems in Engineering*, *2022*(1), 7089914. https://doi.org/10.1155/2022/7089914

[36] Jiao, S., & Sun, Q. (2021). Digital economic development and its impact on econimic growth in China: Research based on the prespective of sustainability. *Sustainability*, *13*(18), 10245. https://doi.org/10.3390/su131810245

[37] Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, *12*(2-3), 231-254. https://doi.org/10.1016/0165-1889(88)90041-3

[38] Kabaklarli, E., Duran, M. S., & ÜçLER, Y. T. (2018). High-technology exports and economic growth: panel data analysis for selected OECD countriesHigh-technology exports and economic growth: panel data analysis for selected OECD countries. Forum Scientiae Oeconomia, 47-60. https://www.ceeol.com/search/article-detail?id=678658

[39] Karki, Y., & Thapa, D. (2021). Exploring the link between digitalization and sustainable development: research agendas. Conference on E-Business, e-Services and e-Society, 330-

341. https://doi.org/10.1007/978-3-030-85447-8_29

[40] Khan, H., & Khan, I. U. (2012). From growth to sustainable development in developing countries: a conceptual framework. *Environmental economics*(3, Iss. 1), 23-31. http://www.irbis-nbuv.gov.ua/cgi-bin/irbis_nbuv/cgiirbis_64.exe?C21COM=2&I21DBN=UJRN&P21DBN=UJRN&IMAGE_FILE_DOWNLOAD=1&Image_file_name=PDF/envirecon_2012_3_1_4.pdf

[41] Kovari, A. (2024). Industry 5.0: Generalized definition key applications opportunities and threats. *Acta Polytechnica Hungarica*, *21*(3), 267-284. https://doi.org/10.12700/APH.21.3.2024.3.17

[42] Kumar, G., Jaisharma, K., & Narendran, R. (2024). Analysis of flight ticket prediction using XGBRegressor optimizer to improve accuracy in comparison with ridge algorithm. AIP Conference Proceedings, 020204. https://doi.org/10.1063/5.0229214

[43] Lei, X., Shen, Z., Štreimikienė, D., Baležentis, T., Wang, G., & Mu, Y. (2024). Digitalization and sustainable development: Evidence from OECD countries. *Applied Energy*, *357*, 122480. https://doi.org/10.1016/j.apenergy.2023.122480

[44] Li, S., Wang, L., & Xue, H. (2023). The Impact of ICT Capital Services on Economic Growth and Energy Efficiency in China. *Energies*, *16*(9), 3926. https://doi.org/10.3390/en16093926

[45] Liew, V. K.-S. (2004). Which lag length selection criteria should we employ? *Economics bulletin*, *3*(33), 1-9. https://ssrn.com/abstract=885505

[46] Luo, S., Yimamu, N., Li, Y., Wu, H., Irfan, M., & Hao, Y. (2023). Digitalization and Sustainable Development: How Could Digital Economy Development Improve Green Innovation in China? *Business Strategy and the Environment, 32*, 1847-1871. https://doi.org/10.1002/bse.3223

[47] Ma, X., Feng, X., Fu, D., Tong, J., & Ji, M. (2024). How does the digital economy impact sustainable development?—An empirical study from China. *Journal of Cleaner Production*, *434*, 140079. https://doi.org/10.1016/j.jclepro.2023.140079

[48] Maddala, G. S., & In-Moo, K. (1999). Unit Roots, Cointegration, and Structural Change. http://doi.org/10.1017/cbo9780511751974

[49] Malik, M. H. (2021). Information technology exports and India's macro-economic indicators. *International Trade, Politics and Development*, *5*(2), 114-135. https://doi.org/10.1108/ITPD-12-2020-0085

[50] Meral, Y. (2019). High technology export and high technology export impact on growth. *International Journal of Business Ecosystem & Strategy (2687-2293)*, *1*(3), 32-38. https://doi.org/10.36096/ijbes.v1i3.283

[51] Mondejar, M. E., Avtar, R., Diaz, H. L. B., Dubey, R. K., Esteban, J., Gómez-Morales, A., Hallam, B., Mbungu, N. T., Okolo, C. C., & Prasad, K. A. (2021). Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet. *Science of The Total Environment*, *794*, 148539. https://doi.org/10.1016/j.scitotenv.2021.148539

[52] Mulenga, R., & Mayondi, M. (2022). Impact of digital services trade on economic growth of developing, emerging and developed countries: P-VAR approach. *American Journal of Economics*, *6*(2), 58-85. https://ideas.repec.org/a/bfy/ojtaje/v6y2022i2p58-85id1053.html

[53] Musa, I., Magaji, S., & Salisu, A. (2023). Mobile telecommunication and economic growth: Evidence from ARDL Modeling. *International Journal of Entrepreneurship, Business and Creative Economy*, *3*(1), 15-31. https://doi.org/10.31098/ijebce.v3i1.1226

[54] Nations., U. (2022). *The Sustainable Development Goals Report 2019. United Nations Publication Issued by the Department of Economic and Social Affairs.* https://unstats.un.org/sdgs/report/2022

[55] Nguyen, H. N., Tran, Q. T., Ngo, C. T., Nguyen, D. D., & Tran, V. Q. (2025). Solar energy

prediction through machine learning models: A comparative analysis of regressor algorithms. *PloS one*, *20*(1), e0315955. https://doi.org/10.1371/journal.pone.0315955
[56] Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. *Journal of Statistical and Econometric methods*, *5*(4), 63-91. https://www.scienpress.com/Upload/JSEM/Vol%205_4_3.pdf
[57] Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S. S., Reuter, U., Gama, J., & Gandomi, A. H. (2020). Data science in economics: comprehensive review of advanced machine learning and deep learning methods. *Mathematics*, *8*(10), 1799. https://doi.org/10.3390/math8101799
[58] OECD. (2011). *Towards Green Growth, OECD Green Growth Studies*. https://doi.org/10.1787/9789264111318-en
[59] OECD. (2019). *Going Digital: Shaping Policies, Improving Lives, OECD Publishing*. https://doi.org/10.1787/9789264312012-en
[60] OECD. (2020). *Digital Transformation in the Age of COVID-19: Building Resilience and Bridging Divides.* . https://img.lalr.co/cms/2020/11/27173400/digital-economy-outlook-covid.pdf
[61] Ozden, E., & Guleryuz, D. (2022). Optimized machine learning algorithms for investigating the relationship between economic development and human capital. *Computational Economics*, *60*(1), 347-373. https://doi.org/10.1007/s10614-021-10194-7
[62] Padhy, N., Dharmireddi, S., Padhy, D. K., Saikrishna, R., & Raju, K. S. (2023). Stock market prediction performance analysis by using machine learning regressor techniques. International Conference on Computing, Communication and Learning, 39-50. https://doi.org/10.1007/978-3-031-56998-2_4
[63] Peng, C., Elahi, E., Fan, B., & Li, Z. (2022). Effect of high-tech manufacturing co-agglomeration and producer service industry on regional innovation efficiency. *Frontiers in Environmental Science*, *10*, 942057. https://doi.org/10.3389/fenvs.2022.942057
[64] Pérez-Martínez, J., Hernandez-Gil, F., San Miguel, G., Ruiz, D., & Arredondo, M. T. (2023). Analysing associations between digitalization and the accomplishment of the Sustainable Development Goals. *Science of The Total Environment*, *857*, 159700. https://doi.org/10.1016/j.scitotenv.2022.159700
[65] Pesaran, M. H., & Shin, Y. (1995). *An autoregressive distributed lag modelling approach to cointegration analysis* (Vol. 9514). Department of Applied Economics, University of Cambridge Cambridge, UK. http://dx.doi.org/10.1017/CCOL0521633230.011
[66] Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289-326. https://doi.org/10.1002/jae.616
[67] Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *biometrika*, *75*(2), 335-346. https://doi.org/10.1093/biomet/75.2.335
[68] Popkova, E. G., De Bernardi, P., Tyurina, Y. G., & Sergi, B. S. (2022). A theory of digital technology advancement to address the grand challenges of sustainable development. *Technology in Society*, *68*, 101831. https://doi.org/10.1016/j.techsoc.2021.101831
[69] Rasiah, R. (2006). Information and communication technology and GDP per capita. *International Journal of internet and enterprise management*, *4*(3), 202-214. https://doi.org/10.1504/IJIEM.2006.010914
[70] Republic, A. (2020). Azerbaijan 2030: national priorities for socio-economic development. https://president.az/en/articles/view/50474
[71] Roger, M., Shulin, L., & Enock, B. (2021). The impact of ICT investment and diffusion on

economic growth: Empirical evidence from Rwanda. *International Journal of Innovation and Economic Development*, *7*(4), 23-36. https://ideas.repec.org/a/mgs/ijoied/v7y2021i4p23-36.html

[72] Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy*, *98*(5, Part 2), S71-S102. http://doi.org/10.1086/261725

[73] Schot, J., & Steinmueller, W. E. (2018). Three frames for innovation policy: R&D, systems of innovation and transformative change. *Research policy*, *47*(9), 1554-1567. https://doi.org/10.1016/j.respol.2018.08.011

[74] Schumpeter, J. A. (1934). The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle. *University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship*. https://ssrn.com/abstract=1496199

[75] Schwarz, G. (1978). Estimating the dimension of a model. *The annals of statistics*, 461-464. https://www.jstor.org/stable/2958889

[76] Singh, A. K., & Jyoti, B. (2023). Impact of digitalization on global sustainable development across countries. *Green and Low-carbon Economy*. https://doi.org/10.47852/bonviewGLCE32021482

[77] Sojoodi, S., & Baghbanpour, J. (2024). The relationship between high-tech industries exports and GDP growth in the selected developing and developed countries. *Journal of the Knowledge Economy*, *15*(1), 2073-2095. https://doi.org/10.1007/s13132-023-01174-3

[78] Storm, H., Baylis, K., & Heckelei, T. (2020). Machine learning in agricultural and applied economics. *European Review of Agricultural Economics*, *47*(3), 849-892. https://doi.org/10.1093/erae/jbz033

[79] Suclle Surco, D. A., Assereto Huamani, A. A., & Herrera-Trujillo, E. A. (2023). Predictive Model for Accurate Horticultural Product Pricing Using Machine Learning. International Conference on Applied Technologies, 231-246. https://doi.org/10.1007/978-3-031-58956-0_18

[80] Tian, Y., & Son, S. (2023). Do ICT service exports and energy imports determine natural resource sustainability? *Resources Policy*, *85*, 103949. https://doi.org/10.1016/j.resourpol.2023.103949

[81] Tóth, P. (2009). ICT diffusion in Hungary Nyuga-Dunántúl region. *Netcom. Réseaux, communication et territoires*(23-1/2), 75-84. https://doi.org/10.4000/netcom.898

[82] UN. (2023). *UN. (2023). The Sustainable Development Goals Report 2023: Special Edition.* . https://unstats.un.org/sdgs/report/2023

[83] Van der Velden, M. (2018). Digitalisation and the UN Sustainable Development Goals: What role for design. *ID&A Interaction design & architecture (s)*(37), 160-174. http://www.mifav.uniroma2.it/inevent/events/idea2010/doc/37_8.pdf

[84] Vu, K. M. (2011). ICT as a source of economic growth in the information age: Empirical evidence from the 1996–2005 period. *Telecommunications policy*, *35*(4), 357-372. https://doi.org/10.1016/j.telpol.2011.02.008

[85] Wang, C.-C., Chien, C.-H., & Trappey, A. J. (2021). On the application of ARIMA and LSTM to predict order demand based on short lead time and on-time delivery requirements. *Processes*, *9*(7), 1157. https://doi.org/10.3390/pr9071157

[86] Wang, X., Kang, Y., Hyndman, R. J., & Li, F. (2023). Distributed ARIMA models for ultra-long time series. *International Journal of Forecasting*, *39*(3), 1163-1184. https://doi.org/10.1016/j.ijforecast.2022.05.001

[87] Wiranatakusuma, D., & Zakaria, Y. (2023). An Analysis the Influence of Mobile Cellular Subscription, Fixed Telephone Subscription, Gross Fixed Capital Formation, and Labor Force

Participation Rate on Gross Domestic Product in Indonesia. Proceedings of the 1st International Conference on Economics and Business, ICEB, 2-3. http://dx.doi.org/10.4108/eai.2-8-2023.2341521

[88] Wu, M.-Y. (2025). Examining the impacts of information and communication technology (ICT) on national development and wellbeing: A global perspective. *Journal of Economy and Technology*, *3*, 190-201. https://doi.org/10.1016/j.ject.2024.11.006

[89] Yang, B., Li, C., Li, M., Pan, K., & Wang, D. (2016). Application of ARIMA model in the prediction of the gross domestic product. 2016 6th international conference on mechatronics, computer and education informationization (MCEI 2016), 1258-1262. https://doi.org/10.2991/mcei-16.2016.257

[90] Yoon, S.-C. (2019). The impact of ICT goods imports on economic growth: Evidence from Asia-Pacific countries. *Journal of Korea Trade*, *23*(7), 1-12. https://ssrn.com/abstract=3533583

[91] Zhang, H. (2023). Prediction and Feature Importance Analysis for Diamond Price Based on Machine Learning Models. Proceedings of the 2nd International Conference on Financial Technology and Business Analysis. 254-259. http://dx.doi.org/10.54254/2754-1169/46/20230347

[92] Zhang, W., Zhao, S., Wan, X., & Yao, Y. (2021). Study on the effect of digital economy on high-quality economic development in China. *PloS one*, *16*(9), e0257365. https://doi.org/10.1371/journal.pone.0257365

[93] Zhou, L. (2021). RETRACTED ARTICLE: Research on economic cost of mineral resources reserve management information system based on GIS remote sensing technology. *Arabian journal of geosciences*, *14*(15), 1475. https://doi.org/10.1007/s12517-021-07756-2