Investigating the Effect of Digital Transformation on the Energy Sector: Saudi Arabia's Case

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Abstract: - In many countries of the world the demand for energy and reliability of renewable energy has risen remarkably with the digital transformation of modern times. For instance, digital technologies such as the Internet of Things, adoption index, and big data analytics are applied to increase efficiency and productivity in the energy sector, along with identifying important interfaces and infrastructure necessary for the efficient and smart functioning of operators and operations, as well as curating an increase in the reliability of tasks and operations while optimizing costs. The purpose of this study is to explore how the integration of digital technologies in the energy sector in Saudi Arabia has led to increased productivity and sustainability on a larger scale. The study focuses on reducing operational costs and improving asset management through digital solutions for monitoring and maintenance. The study covers the period from 2015 to 2022. The findings of the study show that the digital adoption index positively affects GDP growth in the short term with error correction term, but not in the long term without error correction term. Furthermore, the findings indicate that there is no statistically significant relationship between independent variables and GDP growth according to estimates of the long-term results. The null hypothesis is accepted indicating no cointegration between independent variables and GDP growth based on F-statistics being less than I (0) at a 1% significance level. Finally, the trail to explore the nexus of digital technologies and the energy sector in Saudi Arabia is, so far, a new attempt in this area. This is an indication of the originality of this research paper.

Key-Words: - Digital Transformation; Energy Sector; ARDL model; Saudi Arabia; adoption index; GDP growth; operational costs.

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1 Introduction

The integration of digital aspects in the energy sector has improved productivity and sustainability on a larger scale. The demand for energy and the reliability of renewable energy has increased with the digital transformation of modern times. Hence, the output and the financial services of the energy sector are elaborating with the hands of digitalization. Therefore, the present study will be based on the economics of digital transformation in the energy sector in the Kingdom of Saudi Arabia over the period from 2015 to 2022.

Future growth of the energy sector should be primarily driven by digital technology, platform solutions, efficiency, and safety. The electric power business can raise its production capacity, develop new uses for energy resources, boost its efficiency, and improve logistics thanks to emerging digital technology.

Digital transformation in the energy sector in the Kingdom of Saudi Arabia is a key priority for the government. The Kingdom has been investing heavily in digital technologies to drive innovation and efficiency across the energy sector. The government has launched several initiatives to promote digital transformation, such as the National Transformation Program (NTP), which aims to modernize and digitize the public sector. Additionally, Saudi Aramco has launched its digital transformation program, which focuses on improving operational efficiency and customer experience. The government is also investing in smart grid technology, which will enable better monitoring and control of energy consumption. This will help reduce energy waste and improve efficiency. Furthermore, the government is investing in renewable energy sources such as solar and wind power, which will help reduce reliance on fossil fuels.

In addition to these initiatives, the government is also encouraging private companies to invest in digital technologies for the energy sector. Private companies are encouraged to develop innovative solutions that can improve efficiency and reduce costs for consumers. For example, companies are developing software solutions that can monitor energy usage and provide customers with real-time data about their consumption patterns. This data can then be used to optimize energy usage and reduce costs for consumers.

The primary market participants are modifying their strategies in response to rising competition, which is changing methods to energy market regulation and the composition of utilized energy resources. The ongoing procedures are crucial for the Kingdom of Saudi Arabia because their export revenue is dependent on them. The global energy market will need to find new equilibrium points considering the continuing changes, and the Kingdom of Saudi Arabia will need to properly prioritize its future development. The investment of businesses, as well as the recruitment of foreign investment for the realization of projects connected to the introduction of digital technologies, is a crucial factor in the development of the energy sector in the Kingdom of Saudi Arabia.

In the same context, digital transformation in the energy sector can help increase efficiency by streamlining processes and reducing manual labor. This can lead to cost savings and improved customer service. Also, digital transformation can help improve security by providing better data protection and monitoring of energy systems. This can help reduce the risk of cyber-attacks and other security threats. Digital transformation can also help increase reliability by providing real-time monitoring of energy systems, which can help reduce downtime and improve customer satisfaction.

Digital transformation in the energy sector can also help improve sustainability by reducing emissions and increasing renewable energy sources. This can help reduce the environmental impact of energy production and consumption.

The next sections of this research are organized as follows. Section 2 begins with a description of the research problem including the research objective and research hypothesis. A review of previous studies and literature on the research topic is presented in section 3. Section 4 focuses on sketching the data and study model (ARDL) along with its econometric analytical techniques to test the research hypothesis. Section 5 provides details of the research results regarding the impact of digital transformers on the economic growth in the energy sector in the Kingdom of Saudi Arabia in the short-run and long-run as well. Finally, section 6 is devoted to the discussion and conclusion of the research.

2 Statement of the Problem

The digital transformation process in the Kingdom of Saudi Arabia faces a set of problems, and we will mention the most important to bridge this gap, our study will address the following aspects question:

a. What are the necessary interfaces for enabling the smart functioning of the operators?
b. How does digital transformation improve economic development in the Kingdom of Saudi Arabia?

2.1 Research Aim and Objective

The study aims to:

- stating the most important and necessary interfaces and infrastructure for enabling the efficient and smart functioning of the operators and operations.
- curating an increase in the reliability of tasks and operations conducted in the energy sector and optimization of cost.
- digital transformation has the objective of transitioning toward a renewable and low-carbon economy.

2.2 Research Hypotheses

This research addresses two hypotheses:

Hypothesis 1 (H1):
There is no relationship between economic growth and digital transformers in the energy industry.

Hypothesis 2 (H2):
There is no significant impact of the digital transformers on the economic growth in the energy industry.

3 Literature Review

3.1 The Association between Digitalization, Economic Growth and Energy Sector

Many people all over the world are lacking electricity at present times. Therefore, the digitalization of electricity will reduce the cost of electricity on a larger scale, [1]. On the other hand, it has been noted that the revenue and sales of the electric sector have been enhanced while using digitalization. In the Kingdom of Saudi Arabia, the scope of the digital economy has been improved while using AI, big data, IoT, robotics, 5G, and machine learning across both private and public sectors of electricity, [2]. It has been noted that the business operations of the energy sector become easier while making digital transformation effective. The chances of mistakes are reduced at the same time with the incorporation of digital technology.

The initiatives of the $1.2 billion have been used by the youngsters of Saudi Arabia while incorporating the digital aspects in the energy sector, [3]. At the same time, it has been observed that the manpower of the business sector reduces while undertaking the aspects of digitalization in the energy sector. The systems with digital acquisition make more business operations at a time which is fruitful for the respective business growth of the economic sector, [4]. In this way, digital technology enhances the productivity of the energy sector which has an effective role in economic growth. On the contrary, the labor cost of the energy sector decreases with the help of digital transformation.

Digitalization has been suggested to be a key factor in economic progress in developing nations, increasing capital and worker productivity, lowering transaction costs, and allowing access to international markets, [5]. Access to goods and services at cheaper prices is made easier by new technology. It's possible for developing economies to advance faster than industrialized ones. Another example of how the lack of banks in rural regions has made it easier for most impoverished people to receive financial services is mobile banking.

Kenya is an example of a country in Sub-Saharan Africa where mobile banking has made it possible for individuals to transition out of agriculture and into non-farm companies, which may eventually result in higher per capita consumption levels and reduced poverty. In developed countries, digital advancements have higher prospects thanks to network effects in nations with larger networks. Network effects may therefore provide industrialised nations more benefits.

According to, [6], digitalization boosts economic growth through (a) meeting consumer demand for digital goods including computers, communications equipment, and software, and (b) boosting productivity and investments in ICT-using industries. The association between digitalization and economic growth as a comparative analysis of Sub-Saharan Africa and OECD economies is discussed by, [7]. The authors compare Sub-Saharan Africa's (SSA) economic growth to that of OECD nations to determine the impact of digitalization on SSA's economic growth. When measuring the consequences of digitalization, it is important to compare the most and least developed nations to determine whether these effects are dependent on the degree of development of the respective nations.

The adoption of new technologies is thought to have had a significant impact on economic activity in Sub-Saharan Africa. These technologies included e-commerce participation by small and medium-sized enterprises (SMEs), accommodation of the poor majority who were initially financially excluded from mobile banking, and communication accessibility which was hampered by poor infrastructure.

On the other hand, the least developed nations in SSA have been experiencing early deindustrialization because of the consequences of digitalization. In this work, we utilize generalized linear methods of moments (GMM) estimators using a panel dataset including 41 SSA and 33 OECD nations over 11 years, from 2006 to 2016. The findings demonstrate that digitization contributes favorably to economic growth in both sets of nations. Comparing SSA to OECD nations, the impact of broadband internet is negligible, however, the impact of mobile telecommunications is greater in SSA.

According to the authors, these findings are especially intriguing because less developed nations have greater chances due to less technological stagnation. Regarding the policy ramifications, this study suggests that SSA governments increase their investments in ICT and other infrastructures to take advantage of digitalization and achieve meaningful economic growth.

3.2 Enhancement of the Efficiency of the Work Operations

The efficiency of the respective work operations is enhanced with the hands of digital technology, [3]. Hence, it has been noted that the energy sectors of the globalized world are using the theory of digital transformation to obtain better results in their business operations daily. The four main aspects of digital transformation are included with process transformation, domain transformation, the transformation of business model, and cultural transformation. The process transformation improves the quality of the entire business operations. The study evaluates the literature that has already been written about the use of IoT in energy systems in general and smart grids.

Additionally, we go through IoT-enabling technologies including cloud computing and various platforms for data processing. They also discuss privacy and security concerns that arise when using IoT in the energy sector, as well as some potential solutions, such as blockchain technology. The study offers an overview of the role of IoT in energy system optimization for energy policymakers, energy economists, and managers.

Besides this, the cultural transformation will evoke the maintenance of cultural diversity on a broader aspect. Therefore, the transformation of the domain increases the demographic boundaries of the respective business operations. It can be stated that the application of digital technology in the electronics sector will create 3.45 million new jobs between the years 2016 and 2025, [8]. Therefore, a 10.7% growth in the job will be noticed in the electricity industry shortly.

The application of renewable energy will be increased with the digital transformation of the present times. In this way, the energy sector will effectively create 1.07 million new jobs shortly. The management of asset performance and automation will be noticed extensively on a larger scale with the incorporation of efficient digital technologies, [4]. Hence, new employees will be added who have many talents, proper training, and skills in digitized technology. The process of globalization of the energy sector will be noted thus while making business operations with digitized technology.

3.3 Improvement of the Customer Service

It has been observed that the use of digital technology has enhanced the aspects of customer services on a larger scale. As the demands and expectations of modern customers are changing day by day, the employees of the energy sector are trying to make business operations accordingly, [9]. Besides this, the tendency to use online marketing has been evoked within the customers. They are spending more time on online platforms. Therefore, attractive advertisements and easy and frequent feedback from the managing professionals can be noticed while making business operations online. However, satisfied customers provide positive feedback on the online platforms of the energy sector. The number of likes, shares, and comments will be increased on a larger scale with the hands of happy and content customers of the respective energy sector, [10]. Both the business growth and profitability of the business organization will be noticed.

In this way, an integrated service of the customers will be noticed with the incorporation of digitally enabled services and products. The generation of energy and its management becomes easier when using digital technology in the energy sector of the modern world. Moreover, empowerment will be built among the customers for managing their electric consumption on a broader aspect, [2]. The prevention of unwanted incidents is noticed with the hands of digitalized technologies in the energy sectors on a larger scope. Therefore, the study notes effective supply chain management with the hands of digitalization in the energy sectors on a global aspect. It has been noted that customers obtain electric services and products without any barriers or problems in the contemporary situation. As digital technology changes the habits of the customers, they get the energy services exactly at the time of their urgency, [10].

On the other hand, the integration of energy and the management of energy services are noticed exaggeratedly on a larger container with the application of digital technology.

3.4 The Difficulties of using Digital Technologies in the Energy Sector

It has been already discussed that the energy sector is adopting digital technology to increase efficiency and production, but some difficulties are there in the pathway of implementation, [8]. Digitalization implies the inclusion of the latest technologies as per the requirements of the energy producers. Technological innovation intensifies the threat of data stealing and hacking. The energy sectors around the world will implement tech-based supply chains, but the digital supply chain is vulnerable to hacking. On the other hand, the digital economy depends upon tech-savvy people. The authors discussed that the hazards and potential of these technologies for environmental sustainability, as well as political awareness of these risks and opportunities, become increasingly essential with the growing use of information and communication technologies (ICTs) in industrial production.

In this study, we examined the digital and industrial policies of three East Asian and Pacific nations—China, Thailand, and the Philippines—as well as four Sub-Saharan African nations—South Africa, Rwanda, Kenya, and Nigeria—about their expectations regarding the effects of ICTs on industry for environmental sustainability. We expanded upon already-existing frameworks for the evaluation of ICTs that make a distinction between direct environmental effects that happen throughout the ICT's lifecycle and indirect environmental effects that come about because of the use of ICTs in a variety of production processes and economic activities. We investigated and analyzed policy expectations for both the direct and indirect environmental implications of ICTs in the industry using qualitative content analysis.

Also, [8], showed in their study that policies focus more on the good indirect effects of ICT use, such as improved energy efficiency and resource management than on the negative direct effects of ICTs, such as ICT power consumption. Furthermore, expectations varied among nations, and there was no overarching theme that appeared in all regulations. We propose that policymakers should include a deeper systemic knowledge of interconnected direct and indirect consequences and seek targeted initiatives to use ICTs as instruments for environmentally friendly sectors, going beyond awareness of specific potential.

Although businesses should employ digital technologies more often to boost or preserve their competitive edge, they may run across obstacles and problems that prevent them from fully embracing digitalization. As a result, required measures must be taken to address any potential issues, [11]. For instance, despite the oil and gas industry's enthusiasm for adopting BDA, the most difficult difficulties facing the sector are a lack of business support and understanding about big data, the complexity of its applications, and the quality of the data, [12].

Workforce scarcity can create another challenge for the energy sector. A high percentage of labor turnover can impact the growth of the energy sector on a large scale. Carbon footprint reduction is the central concern of the energy sector in the modern period. In this situation, the traditional infrastructure should be replaced by tech-based services. The replacement cost seems to be a burden for organizations. The convenient equipment will be thrown away, which will also cause environmental degradation, [10]. While investigating the digital economy, it is understood that recycling is mandatory to minimize energy consumption. The depletion of natural resources and accumulation of waste are threatening sustainability.

4 Research Methodology

The process used in the research methodology is depicted in Figure 1:

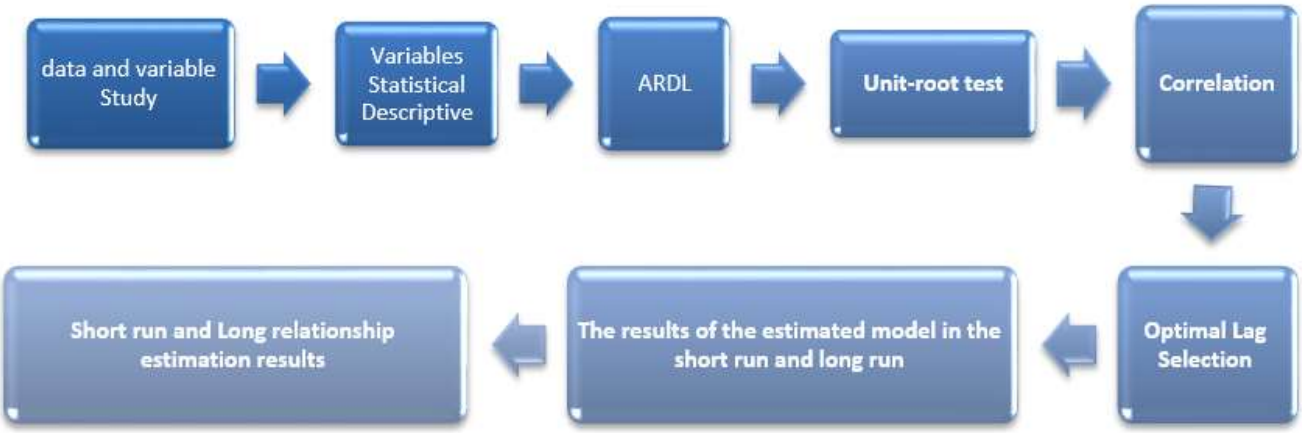

Fig. 1: Steps of Applied Study

4.1 Data

The sample period covers the years from 2015 to 2022. All data used for the variables of this study are secondary data sourced from the World Bank's "World Development Indicators (WDI) database", the Kingdom of Saudi Arabia's statistical annual yearbook reports various years.

Table 1. Variables' definition and description

Variable	Notation	Description and source	Unit
The economic growth	EG_t	EG_t : represents the economic growth and can be calculated by the formula $EG_t = \frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$ When GDP, is GDP per capita in the Kingdom of Saudi Arabia,	
The human capital	l_t	The human capital factor will be calculated by dividing the number of people of working age by the total population of the Kingdom of Saudi Arabia	Percentage of the population
The total invested capital	k_t	Stands for the investment capital factor which is determined by dividing the total invested capital by the gross domestic product in the Kingdom of Saudi Arabia.	% of GDP
The digital adoption index	DAI_t	Stands for the digital adoption index of the Kingdom of Saudi Arabia	
The Government expenditure per GDP	GE_t	Stands for the Government expenditure per GDP of the Kingdom of Saudi Arabia.	% of GDP
Trade ratio per GDP	TR_t	Import-export ratio per GDP of the Kingdom of Saudi Arabia.	% of GDP

Source: World Bank

Regarding the DAI_t stands for the digital adoption index of the Kingdom of Saudi Arabia, reports for digitalization various years, [13]. Table 1 presents the description of the variables, the study data is expanded to monthly data using methods of, [14], [15].

4.2 The Econometric Model

A simple regression model will then be applied for analysis of the linear relationship between digital transformation and economic growth as the fundamental econometric model. This will help to generate the best-fit line between the two available data sets and then evaluate these datasets to analyze how far each of the different data points is distributed from one another. Eviews (V.12) software packages will be used for further statistical analysis. Assess the risk that correlations can develop accidentally, these software tools can also quickly evaluate for statistical significance. A variety of techniques to gauge the reliability of the predictions made will also be done, including R-squared, t-tests, p-values, and null hypothesis testing.

The impact of digital transformation on economic growth can be assessed by using a model adapted from the Cobb-Douglas function. The Cobb-Douglas function is as follows:

$$Y_t = A \times (k_t)^{\alpha} \times (l_t)^{(1-\alpha)}, when\ 0 < \alpha < 1 \quad (1)$$

When Y, is the economic growth in the Kingdom of Saudi Arabia. The number of persons who are working age divided by the overall population will be used to compute the human capital factor (l_t). Additionally, the investment capital component (k_t) is calculated by dividing the entire amount of invested capital by the GDP.

By taking the Cobb-Douglas function's natural logarithm, the prior model will be calculated. The growth model they suggest has the following structure:

$$EG_t = \beta_0 + \beta_1 \ln(k_t) + \beta_2\, ln(l_t) + \varepsilon_t \quad (2)$$

When

EG_t: represents the dependent variable which is calculated by the formula

$$EG_t = \frac{GDP_t - GDP_{t-1}}{GDP_{t-1}} \quad (3)$$

when GDP is GDP per capita in the Kingdom of Saudi Arabia. These elements will not promote economic growth as they did in the past when human capital and investment capital were fully used. There will be a slowing or a decline in economic growth. Recent empirical work, however, demonstrates that the digital transition is essential for fostering economic growth. It is concluded that the growth model, which is represented as follows, should incorporate the digital transformation variable (DAI_t) as well as the government expenditure (GE_t) and the trade openness ($Trade\_ratio_t$) World Bank database as follows:

$$EG_t = \beta_0 + \beta_1 \ln(k_t) + \beta_2 \ln(l_t) + \beta_3 DAI_t + \beta_4 GE_t + \beta_5 Trade\_ratio_t + \varepsilon_t \quad (4)$$

so, the variables can be stated as follows:

EG_t : represents the economic growth and can be calculated by the formula $EG_t = \frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$ when GDP is GDP per capita in the Kingdom of Saudi Arabia, the source of the data is the World Bank database.

l_t: represents the human capital factor that will be calculated by dividing the number of people of working age by the total population in the Kingdom of Saudi Arabia, the source of the data is the World Bank database.

k_t: stands for the investment capital factor which is determined by dividing the total invested capital by the gross domestic product in the Kingdom of Saudi Arabia, the source of the data is the World Bank database.

DAI_t: stands for the digital adoption index of the Kingdom of Saudi Arabia, reports for digitalization various years, [13].

GE_t: stands for the Government expenditure per GDP of the Kingdom of Saudi Arabia, the source of the data is the World Bank database.

$Trade\ ratio_t$: trade ratio per GDP of the Kingdom of Saudi Arabia, the statistical World Bank database.

The Variance Inflation Factor (VIF) test was carried out before performing the regression analysis to assess the quality and validity of the estimated models to make sure that the independent variables of the study did not suffer from the problem of multicollinearity as this problem may result in several unacceptable outcomes such as inaccurate regression coefficients, failing to reach statistical significance, changing in the estimated signs of coefficients, or suboptimal estimates. Table 2 shows the descriptive statistics for the dependent and independent variables. The table presents that the mean of the growth GDP in the Kingdom of Saudi Arabia over the period from 2015 to 2021 (monthly data) is 0.855248 with a corresponding standard deviation of 2.868544 and minimum value of -5.148737 and maximum value of 5.450610. In the same context, the mean of the government expenditure over the studying period is 29.56721 with a standard deviation of 3.386348, and minimum value of 21.28417, and a maximum value of 36.33841.

Also, the mean of the total invested capital over the studying period is 28.67747 % with a standard deviation of 3.214596, and minimum value of 22.75899 %, and a maximum value of 34.94470 %. Moreover, the mean of the human capital over the study period is 56.93429 % with a standard deviation of 2.557821, and minimum value of 53.73279 %, and a maximum value of 61.68677 %. Regarding the trade ratio, the mean of the variable over the studying period is 62.20286 % with a standard deviation of 5.678439, and minimum value of 50.49131 %, and a maximum value of 73.74334 %. In the same context, the most important variable in the independent variable is the digital adoption index has a mean over the studying period of 80.26145 of the population with a standard deviation of 56.62212 and a minimum value of 56.62212 % and a maximum value of 96.04888 %.

The study data can be sketched as follows (Figure 2):

Table 2. Variables Statistical Descriptive

variables	GDP_ GROWTH	GET	KT	LT	TRADE RATIO	DAI
Mean	0.8552	29.567	28.677	56.934	62.202	80.261
Median	1.2069	29.058	28.830	55.941	63.437	89.578
Maximum	5.4506	36.338	34.944	61.686	73.743	96.048
Minimum	-5.1487	21.284	22.758	53.732	50.491	56.622
Std. Dev.	2.8685	3.3863	3.2145	2.5578	5.6784	14.973
Skewness	-0.4301	-0.158	0.1508	0.5393	-0.2573	-0.3815
Kurtosis	2.3722	3.3497	2.4974	1.8724	2.9929	1.3722
Jarque-Bera	3.9691	0.7795	1.2025	8.5223	0.9275	11.311
Probability	0.1374	0.6772	0.5481	0.0141	0.6289	0.0034
Sum	71.840	2483.6	2408.9	4782.4	5225.04	6741.9
Sum Sq. Dev.	682.96	951.79	857.69	543.02	2676.38	18607.9
Observations	96	96	96	96	96	96

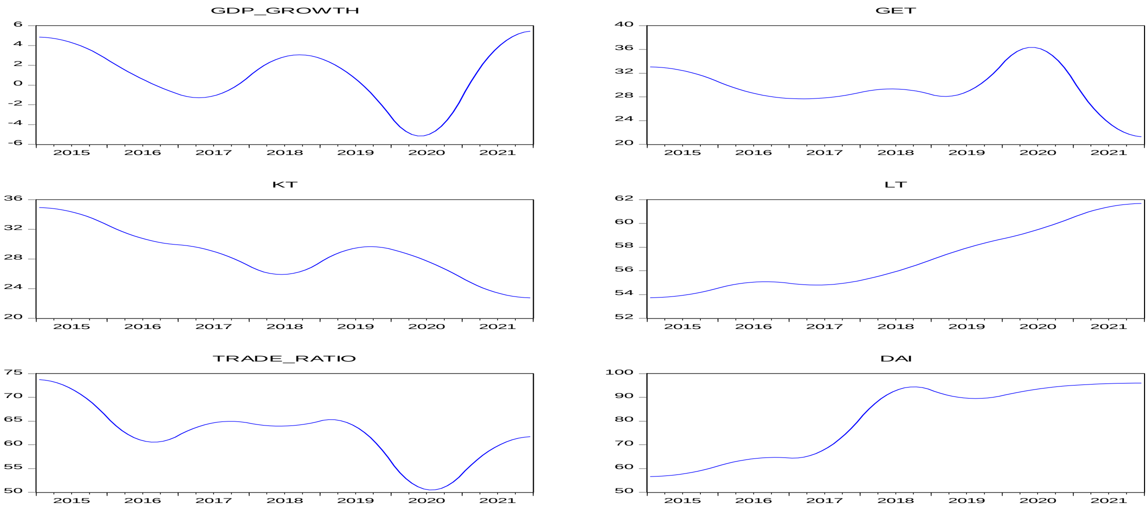

Fig. 2: The time series graphs of the study data

4.3 Study Model

This study applied the ARDL model, one of the most current dynamic models that takes the factor of time into account, to evaluate the study's hypotheses using econometrics analytical technique. to determine the variables' short- and long-term relationships. As an implicit equation, the following describes the association between economic growth and digital transformers, the Government expenditure per GDP of the Kingdom of Saudi, in the energy industry as well as the human capital factor (l_t). Additionally, the investment capital component (k_t).

$$EG_t = \text{f}\left((\ln(k_t)\,, ln(l_t)\,, DAI_t, GE_t \text{ and } TO_t\right) \quad (5)$$

4.4 Applied Study

The steps that were followed can be illustrated according to the steps:

4.4.1 Unit-root Test

Table 3 shows the results of unit root tests, We employ the unit root test of, [16], [17], to assess the stationarity of time series for the research variables. Given the results in Table 5, we can use the ARDL model to determine the short- and long-term relationships between the study variables because our variables are mixed between being integrated of different orders, i.e., order zero, I(0), and order one, I(1), and there are no variables integrated of order two, I(2), [18].

$$DEG_t = \beta_0 + \beta_1 \,\text{Dln}(k_t) + \beta_2 D\, ln(l_t) + \beta_3 DDAI_t + \beta_4 DGE_t + \beta_5 DTO_t + \varepsilon_t \quad (6)$$

According to the previous model in equation 6. It's expected that all independent variables (digital transformers, the Government expenditure per GDP of the Kingdom of Saudi, as well as the human capital factor (l_t), the investment capital component (k_t) and the trade ratio has positive associations with dependent variables (GDP growth). This association can be presented by the correlation matrix as follows:

4.4.2 Correlation

A. Correlation Matrix

The linear correlation (multicollinearity) between the independent variables is one of the most significant issues that conventional models and regression analysis face. It has to do with the OLS method's assumption that the independent variables in the regression model would not be strongly correlated with one another, making it difficult to distinguish between their impacts on the dependent variable, [19]. There are various signs to look for this issue, [20]. We may utilize the correlation matrix between the independent variables and the variance-inflation factor as one of these indications (VIF). Severe multicollinearity is indicated by a VIF of more than 10 and an excess of 0.8 in the pairwise or zero-order correlation coefficient between two regressions, [21].

As from Table 4, the Correlation Matrix indicates that there is no multicollinearity between independent variables as long as the Pearson correlation coefficient less is than (0.8). In the same context, there is a positive correlation coefficient between economic growth variables in the Kingdom of Saudi Arabia and the variables Trade ratio, DAI. On the other hand, there is a negative correlation coefficient between the economic growth variable in the Kingdom of Saudi Arabia and the variables government expenditure and investment capital factor.

Table 3. Phillips & Perron and Augmented Dickey-Fuller tests for series stationarity

UNIT ROOT TEST TABLE (PP)							
variables		GDP GROWTH	GET	lnKT	lnLT	TRADE RATIO	DAI
At Level	t-Statistic	-1.5534	-1.1115	-2.5281	5.5842	-0.9749	1.9725
	Prob.	0.1125	0.24	0.0119	0.9995	0.2925	0.988
	stationarity	No	No	No	No	No	No
At First Difference	t-Statistic	-1.9815	-1.9959	-1.951	-2.017	-2.0433	-1.8096
	Prob.	0.0427	0.0446	0.043	0.032	0.02	0.0671
	stationarity	Yes	Yes	Yes	Yes	Yes	Yes
UNIT ROOT TEST TABLE (ADF)							
At Level	t-Statistic	-2.9123	-0.8655	-1.799	2.0537	-0.8993	1.5597
	Prob.	0.0041	0.3381	0.0686	0.9901	0.3237	0.9701
	stationarity	Yes	No	No	No	No	No
At First Difference	t-Statistic	-3.5736	-3.727	-3.0569	-1.998	-3.7561	-3.1337
	Prob.	0.0005	0.0003	0.0026	0.0407	0.0003	0.0021
	stationarity	Yes	Yes	Yes	Yes	Yes	Yes
Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant							
*MacKinnon (1996) one-sided p-values.							

Table 4. Correlation Matrix Result pairwise correlations

Probability		GDP GROWTH	LNKT1	LNLT1	TRADE RATIO1	DAI1	GET1
GDP_GROWTH1	Correlation	1					
LNKT1	Correlation	-0.419910	1				
	Probability	0.0001	-----				
LNLT1	Correlation	0.195708	0.147631	1			
	Probability	0.0762	0.1829	-----			
TRADE_RATIO1	Correlation	0.796142	-0.000679	-0.080445	1		
	Probability	0.0000	0.9951	0.4697	-----		
DAI1	Correlation	0.280050	-0.533336	-0.115267	-0.111008	1	
	Probability	0.0103	0.0000	0.2994	0.3178	-----	
GET1	Correlation	-0.741280	0.314229	-0.187387	-0.698544	0.218410	1
	Probability	0.0000	0.0038	0.0898	0.0000	0.0473	-----

After the multicollinearity variables have been dropped, VIF shows that there is no multicollinearity between the rest of the independent variables as long as the variance coefficient is less than 10 (Table 5).

B. Variance Inflation Factors (VIF)

Table 5. Variance Inflation Factors (VIF)Test Results

Variables	VIF	Tolerance
GET1	4.92	0.203
trade ratio1	3.26	0.307
KT1	3.068	0.326
DAI1	2.296	0.436
LT1	1.414	0.707

4.4.3 Optimal Lag Selection

To determine the optimal lag length needed for the model's variables present in Table 6, we use different criteria such as Akaike's Information Criterion (AIC), Hannan-Quinn Information Criterion (HIC), and Schwarz Information Criterion (SIC), [17], as shown in Table 8. Schwarz's criterion and Akaike's criterion show that the lag period is the second period.

4.4.4 ARDL Approach

The research utilized the autoregressive distributed lag (ARDL) approach, a notable method developed by, [22]. This approach is widely regarded as the most effective econometric technique when dealing with variables that are either stationary at I(0) or integrated of order I(1). Given the specific objectives of the study, the ARDL model is considered superior to alternative models in capturing both the short-term and long-term effects of digital transformation on the energy sector, we are using the Bounds Testing Approaches to the Analysis of Level Relationships and Autoregressive Distributed-Lag (ARDL) techniques, [22]. One of the newest dynamic models that considers the element of time is the ARDL model. We analyze long-run correlations between variables based on time series data to pinpoint the short- and long-term linkages between the variables as well as the rate at which the system will reach equilibrium. Two elements make up this model: (1) Autoregressive (AR) models, which employ the dependent variable as a lagged independent variable, and (2) Distributed Lagged (DL) models, which show that the dependent variable also influences.

Table 6. Optimal Lag Selection Results

Lag	LogL	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	34.97180	NA	1.86e-08	-0.772581	-0.587182	-0.698554
1	1214.395	2138.688	1.07e-21	-31.26387	-29.96608	-30.74568
2	1414.494	**330.8304***	**1.37e-23***	**-35.63985***	**-33.22966***	**-34.67749***
3	1421.687	10.74075	3.09e-23	-34.87165	-31.34907	-33.46512
4	1430.302	11.48696	7.03e-23	-34.14139	-29.50641	-32.29069
5	1440.869	12.39816	1.62e-22	-33.46316	-27.71579	-31.16830
6	1454.031	13.33738	3.82e-22	-32.85415	-25.99438	-30.11512
7	1470.643	14.17561	9.41e-22	-32.33714	-24.36498	-29.15394
8	1493.013	15.51036	2.43e-21	-31.97369	-22.88913	-28.34633

** Indicates lag order selected by the criterion*

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

The equation 7 shows the ARDL model for our study, as follows:

$$\Delta \mathrm{GDP\_GROWTH}_{\,t} = \alpha_0 + \alpha_1 \mathrm{GDP\_GROWTH}_{t-1} + \alpha_2\, l\_KT_{t-1} + \alpha_3\, l\_LT_{t-1} + \alpha_4\, TRADE\_RATIO_{t-1} + \alpha_5\, \mathrm{DAI}_{t-1} + \sum_{j=1}^{p} \beta_{1j} \Delta l\_GDP\_GRPWTH_{t-j} +$$

$$\sum_{j=0}^{q} \beta_{2j}\Delta l\_KT_{t-j} + \sum_{j=0}^{r} \beta_{3j}\Delta l\_LT_{t-j} + \sum_{j=0}^{m} \beta_{4j}\Delta \text{TRADE\_RATIO}_{t-j} + \sum_{j=0}^{k} \beta_{5j}\Delta \text{DAI}_{t-j} + \mu_{it} \quad (7)$$

where (Δ) refers to the first-difference operator; p, q, r, m, and k indicate lags; (α1 – α5) refers to long-run parameters; (β1 – β5) refers to short-run parameters; (α0) refers to the intercept; (μt) refers to the error term.

The short-run effects are estimated from the equation 8

$$\Delta \text{GDP\_GROWTH}_{t} = \alpha_0 + \sum_{j=1}^{p} \beta_{1j}\Delta l\_GDP\_GROWTH_{t-j} + \sum_{j=0}^{q} \beta_{2j}\Delta l\_KT_{t-j} + \sum_{j=0}^{r} \beta_{3j}\Delta l\_LT_{t-j} + \sum_{j=0}^{m} \beta_{4j}\Delta \text{TRADE\_RAIO}_{t-j} + \sum_{j=0}^{k} \beta_{5j}\Delta \text{DAI}_{t-j} + \varphi \text{ECT}_{t-1} + \mu_{it} \quad (8)$$

φECT_{t-1} represents the speed of adjustments towards long-run equilibrium, which means that if the system is moving out of equilibrium in one direction, then will pull it back to equilibrium, [17]. "A divergence is shown by a positive coefficient, and convergence is indicated by a negative coefficient. When the estimate of ECt is 1, 100% of the adjustment occurs during the period or is immediate and complete. When the estimate of ECt is 0.5, 50% of the adjustment occurs throughout each period or year. It is no longer logical to assert that there is a long-run connection when ECt = 0, which demonstrates that there has been no adjustment, [18].

The selected model of ARDL by using (the SIC) criterion to determine the lags gave significant coefficient estimation results for the (DAI1(-2)) variable in the short run. On the other hand, the selected model did not give significant coefficient estimation results for all independent variables in the long run as Table 7 shows. To ensure the stability of the model, we refer to Cumulative Sum (CUSUM) as well as Cumulative Sum of Squares (CUSUMSQ) graphs (Figure 3). Since the two diagrams in Figure 3 show that all the plotted points were between the two red-colored bounds that mean the used model was stable.

A. ARDL Model Estimation in the short run and long run

Table 7. ARDL Model Estimation in the short run and long run

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
GDP_GROWTH1(-2)	-0.851580	0.066602	-12.78606	0.0000
KT1(-2)	-0.282575	0.039887	-7.084353	0.0000
LT1(-2)	2.221167	0.223161	9.953204	0.0000
TRADE_RATIO1(-2)	0.492708	0.036914	13.34735	0.0000
DAI1(-2)	0.200510	0.022195	9.033895	0.0000
GET1(-2)	0.075727	0.034485	2.195931	0.0318
C	-0.002684	0.001644	-1.632789	0.1075
R-squared	0.999988	Mean dependent var		0.008527
Adjusted R-squared	0.999984	S.D. dependent var		0.438440
S.E. of regression	0.001731	Akaike info criterion		-9.686622
Sum squared resid	0.000189	Schwarz criterion		-9.154522
Log-likelihood	410.3082	Hannan-Quinn criter.		-9.473137
F-statistic	301754.0	Durbin-Watson stat		2.073334
Prob(F-statistic)	0.000000			

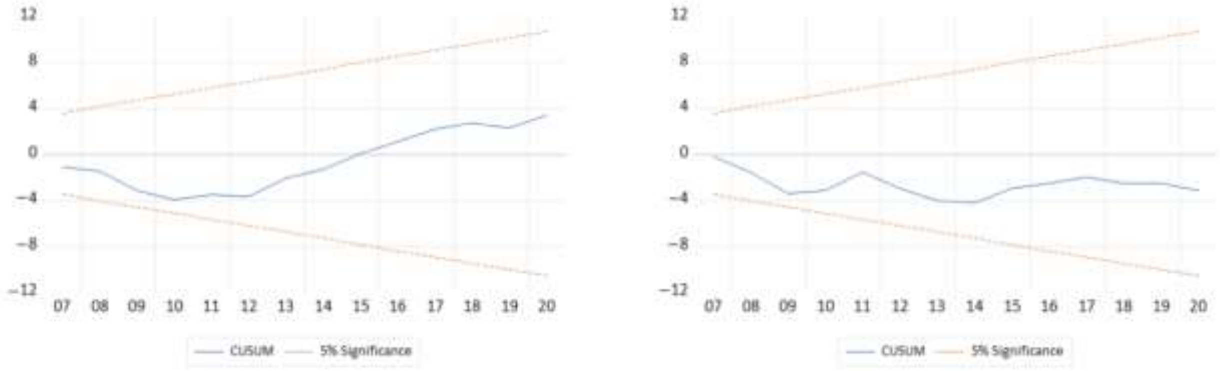

Fig. 3: Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMQ)

4.4.5 The Results of the Estimated Model in the Short Run

The analysis of short-run and long-run relationships is based on the result in Table 8. Estimates indicate in the short run that all independent variables have a significant influence on the growth of the GDP in Saudi Arabia. In detail, the variables the human capital, the digital adoption index, and the Government expenditure per GDP have significant positive impacts on the dependent variable GDP growth. On the other hand, the variables and the total invested capital have a significant negative impact on the dependent variable GDP growth. In detail, whenever the digital adoption index increases by one unit, the GDP Growth increases by approximately (20%).

B. ARDL Model Estimation in the short run and long run using error correction

Table 8. ARDL Model Estimation in the short run and long run using error correction

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
GDP_GROWTH1(-2)	-1.034681	0.029837	-34.67733	0.0000
KT1(-2)	-0.297741	0.015404	-19.32833	0.0000
LT1(-2)	2.476733	0.090698	27.30756	0.0000
TRADE_RATIO1(-2)	0.579563	0.016479	35.16976	0.0000
DAI1(-2)	0.255272	0.009204	27.73612	0.0000
GET1(-2)	0.055870	0.012639	4.420278	0.0000
DEQ1(-2)	0.242386	0.038474	6.300074	0.0000
C	-0.002504	0.000760	-3.296092	0.0017

R-squared	0.999999	Mean dependent var	0.013681
Adjusted R-squared	0.999998	S.D. dependent var	0.446058
S.E. of regression	0.000627	Akaike info criterion	-11.68494
Sum squared resid	2.24E-05	Schwarz criterion	-11.05044
Log-likelihood	476.7126	Hannan-Quinn criter.	-11.43094
F-statistic	1945590.	Durbin-Watson stat	0.875527
Prob(F-statistic)	0.000000		

Long run estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
KT1	-0.223983	0.119612	-1.872586	0.0663
LT1	1.345285	0.449493	2.992893	0.0041
TRADE_RATIO1	0.419437	0.049108	8.541074	0.0000
DAI1	0.254884	0.030620	8.324138	0.0000
GET1	-0.167027	0.083341	-2.004133	0.0498
DEQ1	136.0574	34.65313	3.926266	0.0002
C	-0.213499	0.030095	-7.094071	0.0000

4.4.6 The Results of the Estimated Model in the Long Run

Estimates of long-term results reveal that there is a statistically significant relationship for all independent variables.

4.4.7 Short-run Relationship Estimation Results

Estimates of Short-run results in Table 8, detect that there is a statistically significant and non-negative economic link for the variable, this means that the relationship is positive in the short-term. Estimates indicate in the short run that total invested capital significantly affects the GDP growth in Saudi Arabia, and the parameter of total invested capital is negative, which means that there is an indirect relationship between gross domestic product and total invested capital. On the other hand, human capital, digital adoption index, Government expenditure per GDP, and trade ratio per GDP affect the GDP growth in Saudi Arabia, and the parameters of these variables are positive, which means that there is a direct relationship between gross domestic product and these variables. In detail, Whenever the digital adoption index increases by one unit, the GDP Growth increases by approximately (5%), About the results of the error correction model (ECM), Table 8. This shows that the error correction term (DEQ1(-2)) is highly significant at the specified level of significance, 5%, this indicates the existence of a long-term equilibrium relationship cointegration relationship among the model variables. The coefficient of (DEQ1(-2)) approximately equals (0.24). This means that deviations in the short-run are corrected by approximately 24% within one year towards the long-run equilibrium relationship.

4.4.8 Long-run Relationship Estimation Results

Estimates of long-term results shown in Table 8, reveal that there is a statistically significant and positive economic relationship between human capital, digital adoption index, Government expenditure per GDP, and trade ratio per GDP affects the GDP growth in Saudi Arabia, and the parameters of these variables are positive, which means that there is a direct relationship between gross domestic product and these variables. In detail, Whenever the digital adoption index increases by one unit, the GDP Growth increases by approximately (25%).

4.4.9 Bounds Test

Table 9, shows the existence of the covariance relationship (long-run relationships) in the (ARDL) model, the bounds test is used, and the significance of this test is recognized by its F-Statistic value, [18]. Since the computed (F-statistic) value is smaller than the lower bound, I (0), of the critical values at the 1% significance level, the result suggests that there is no cointegration connection. The absence of a long-run equilibrium connection, or the null hypothesis H0, which claims that there is no cointegration, is thus accepted.

4.4.10 ARDL Diagnostic Tests

The following table shows the diagnostic tests of residual distribution, autocorrelation, and identification problems. Going to Table 12, the results indicate that: 1) the residuals of this model are normally distributed lines Figure 3, [21], [23], where H0 is accepted from the Jarque-Bera statistic because the corresponding p-value is greater than 5 % significance level. 2) there is no serial correlation, [21], [24], where the H0 acceptance from the Breusch-Godfrey (BG) test for LM serial correlation (Autocorrelations) is accepted because the corresponding p-value is greater than 5%. 3) H0 acceptance of the Ramsey RESET test (regression specification error test) to detect general functional form misspecification, [20]. But regarding the heteroscedasticity, [21], it failed to reject H0 from the Breusch-Pagan-Godfrey (BPG) test as Table 10, depicts.

Table 9. Bounds Test Result

F-Bounds Test **Null Hypothesis: No levels of relationship**

Test Statistic	Value	Signif.	I (0)	I (1)
F-statistic	1.477730	10%	2.08	3
K	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

Table 10. ARDL Diagnostic Tests Result

Residuals Distributed	Normality Test (Jarque-Bera)	0.627	0.731
Serial Correlation	LM Test/ Breusch-Godfrey (BG)	0.281639	0.7555
Heteroskedasticity	Breusch-Pagan-Godfrey Test (BPG)	0.842591	0.6399
Stability	Ramsey RESET Test	0.851254	0.3598

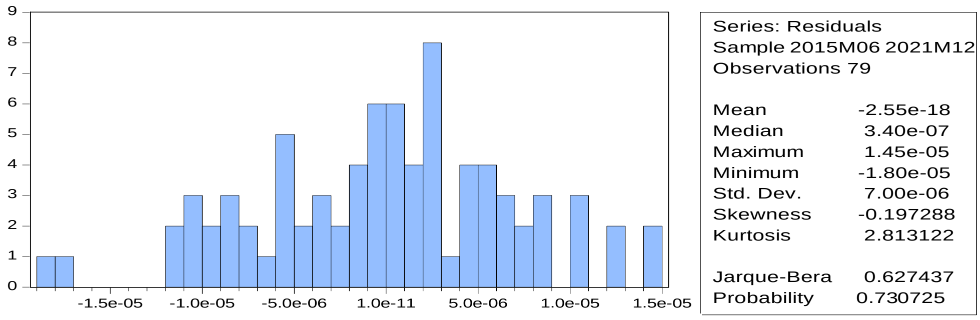

Fig. 4: Jarque- Bera Normality Test

5 Results

5.1 Unit-root Test:

After considering the AIC criterion, the study variables in the time series stationarity test (unit root test) indicate that they are at level I (0) or at the first difference, I (1), allowing us to use the ARDL methodology to determine the short- and long-term relationships between the variables.

5.2 Econometric Model

The growth model they suggest has the following structure:

$$EG_t = \beta_0 + \beta_1 \ln(k_t) + \beta_2\, ln(l_t) + \varepsilon_t \quad (9)$$

When, EG_t: represents the dependent variable which is calculated by the formula.

$$\mathrm{EG_t} = \frac{\mathrm{GDP_t} - \mathrm{GDP_{t-1}}}{\mathrm{GDP_{t-1}}} \quad (10)$$

when GDP is GDP per capita in the Kingdom of Saudi Arabia. These elements will not promote economic growth as they did in the past when human capital and investment capital were fully used. There will be a slowing or a decline in economic growth. however, demonstrates that the digital transition is essential for fostering economic growth. It is concluded that the growth model, which is represented as follows, should incorporate the digital transformation variable (DAI_t) as well as the government expenditure (GE_t) and the trade openness ($Trade\_ratio_t$) World Bank database.

5.2.1 Optimal Lag Selection

To determine the ideal length of the ARDL model variables, the (SIC) criterion with one lag period was initially used. However, it did not produce results of estimates that were symmetrical with the variables and model of the study, so the (AIC) criterion with the lowest value that was selected by (2) lags was chosen to finish the study.

5.2.2 ARDL Approach

In this work, we are using the Bounds Testing Approaches to the Analysis of Level Relationships and Autoregressive Distributed-Lag (ARDL) techniques, [22]. One of the newest dynamic models that considers the element of time is the ARDL model. We analyze long-run correlations between variables based on time series data to pinpoint the short- and long-term linkages between the variables as well as the rate at which the system will reach equilibrium. Two elements make up this model: (1) Autoregressive (AR) models, which employ the dependent variable as a lagged independent variable, and (2) Distributed Lagged (DL) models, which show that the dependent variable also influences.

5.2.3 ARDL Model Estimation in the Short Run and Long Run

The selected model of ARDL by using (the SIC) criterion to determine the lags gave significant coefficient estimation results for the (DAI1(-2)) variable in the short run. On the other hand, the selected model did not give significant coefficient estimation results for all independent variables in the long run.

5.2.4 Bounds Test:

According to the results in the table, the F-statistic is equal to (1.477730) less than I (0) which is equal to 3.06 at 1% Significantly, we accept H0, that there is no cointegration between the independent variables and the GDP GROWTH.

6 Discussion and Conclusion

The sample period covers the years from 2015 to 2022 (8 years) of the Saudi economy. All data used for the variables of this study are secondary data sourced from the World Bank's "World Development Indicators (WDI) database. Regarding the stands for the digital adoption index of the Kingdom of Saudi Arabia, reports for digitalization various years, [13]. The study data is expanded to monthly data using methods of, [15], [16].

Hypothesis 1 (H1): There is no relationship between economic growth and digital transformers in the energy industry.

The study results show that the Correlation Matrix indicates that there is no multicollinearity between independent variables as long as the Pearson correlation coefficient is less than (0.8). In the same context, there is a positive correlation coefficient between economic growth variables in KSA and the variable's Trade ratio, DAI. In detail, there is a significant positive correlation between the economic growth variable and digital transformers in the energy industry with a significant positive Pearson correlation coefficient of 0.280050.

Hypothesis 1 (H2): There is no significant impact of the digital transformers on the economic growth in the energy industry.

Estimates indicate in the short run that all independent variables have a significant influence on the growth of the GDP in Saudi Arabia. In detail, the variables the human capital, the digital adoption index, and the Government expenditure per GDP have significant positive impacts on the dependent variable GDP growth. On the other hand, the variables and the total invested capital have a significant negative impact on the dependent variable GDP growth.

Table 11. Coefficient of DAI in the long run and short run with and without error correction

STATISTICS	Without error correction		With error correction	
	Short run	Long run	Short run	Long run
coefficient	0.201	0.112	0.056	0.25
T-test	9.03	0.504	4.42	8.324
p-value	0.000	0.0616	0.000	0.000

As the results in Table 11, the estimates of the variables in the short and long run, it is noted that the digital adoption index positive to the increase in GDP growth in the long term with error correction term while it did not give any effect on GDP growth in the long term without error correction term. On the other hand, it is noted that the digital adoption index is positive to the increase in GDP growth in the short term with error correction term and without error correction term.

Estimates of long-term results reveal that there is no statistically significant relationship for all independent variables. According to the results in the table, F-statistics equal to (1.477730) less than I(0) which is equal to 3.06 at 1% Significant, We accept H0, that there is no cointegration between the independent variables and the GDP GROWTH.

Bounds Testing Approaches to the Analysis of Level Relationships and Autoregressive Distributed-Lag (ARDL) approaches are being used in this study, [22]. The ARDL model is one of the most recent dynamic models that take time into account. To determine the short- and long-term connections between the variables as well as the pace at which the system will attain equilibrium, we analyze long-run correlations between variables based on time series data. This model consists of two components: The dependent variable is used as a lagged independent variable in (1) autoregressive (AR) models, and (2) distributed lag (DL) models, which demonstrate that the dependent variable also impacts. The selected model of ARDL by using (the SIC) criterion to determine the lags gave significant coefficient estimation results for the (DAI1(-2)) variable in the short run. On the other hand, the selected model did not give significant coefficient estimation results for all independent variables in the long run.

Table 10 shows the diagnostic tests of residual distribution, autocorrelation, and identification problems. Returning to Table 11, the results indicate that: *First*, the residuals of this model are normally distributed lines Figure 4, [20], [22], where H0 is accepted from the Jarque-Bera statistic because the corresponding p-value is greater than 5% significance level. *Second*, there is no serial correlation, [23], [20]. where the H0 acceptance from the Breusch-Godfrey (BG) test for LM serial correlation (Autocorrelations) is accepted because the corresponding p-value is greater than 5%. *Third*, H0 acceptance of the Ramsey RESET test (regression specification error test) to detect general functional form misspecification, [19]. But regarding the heteroscedasticity, [20], it failed to reject H0 from the Breusch-Pagan-Godfrey (BPG) test.

Overall, digital transformation has the potential to revolutionize the energy sector in Saudi Arabia by improving efficiency, sustainability, and resilience. However, challenges such as cybersecurity risks and policy implementation need to be addressed for the successful integration of digital solutions into the respective industry.

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Conflict of Interest

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