JOURNAL OF POLITICAL STABILITY ARCHIVE

Online ISSN: 3006-5879 **Print ISSN:** 3006-5860
DOI: https://doi.org/10.63468/jpsa.4.1.17
Vol. 4 No. 1 (2026)
https://journalpsa.com.pk/index.php/JPSA/about

Recognized by: Higher Education Commission (HEC), Government of Pakistan

Artificial Intelligence Innovation and Natural Resource Management: An ARDL Analysis of Economic Growth in Pakistan

Farhana Naz*
Lecturer (Economics), Department of Economics, International institute of Islamic Economics, International Islamic University, Islamabad
farhana.naz@iiu.edu.pk

Dr. Safia Begum
Associate Professor of Economics, Higher Education Department
safiakakakhail@gmail.com

Dr. Nasiha Begum
Principal, Education Department, Workers Welfare Board, KP. Pakistan
shisan786@gmail.com

Zia Ullah Khan
Department of Economics, Hazara University, Mansehra, Pakistan
ziaullahk310@gmail.com

*Corresponding Author

ABSTRACT

This study examines the impact of artificial intelligence (AI) innovation and natural resource management on Pakistan's economic growth from 1990 to 2024. The time-series econometric technique, the autoregressive distributed lag (ARDL) model, was used to analyze short- and long-term relationships among economic growth, AI innovation (proxies by patent applications), total natural resource rents, and inflation. The results show that AI innovation and natural resource rents significantly contribute to economic growth, while inflation negatively affects it. These findings highlight the importance of promoting AI-driven technological advancements and sustainable resources used to achieve long-term financial resilience. Based on the results, this study recommends policies to reward AI innovation and adopt sustainable natural resource management practices, ensuring a balanced and robust pathway for economic development.

Keywords: ARDL; Artificial Intelligence; Sustainable growth; Natural resources

INTRODUCTION

The concept of artificial intelligence (AI) has advanced rapidly from theory to a vital part of contemporary economies. Every field, including education, economics, medicine, and others, is continually advancing through scientific and technological advances. Therefore, rapid economic growth and wealth accelerated the development of econometrics and statistics, and related fields have expanded further, making it more difficult for authorities to control the economy. Also, economic advancement is significantly influenced by economic management and structure. Thus, it disrupts the orderly operation of the economic development process (Maksanova et al., 2021). Besides providing new development opportunities for institutions, the AI era opens new avenues for innovation- and entrepreneurship-focused education. Artificial intelligence (AI) technologies, including robotics, machine learning, and natural language processing, have significantly increased productivity, reduced operating expenses, and opened new business opportunities. Thus, the combination of economic expansion and artificial intelligence (AI) promotes the development of technology for economic control and management. Similarly, it encourages the use of technology in economic policies, confirming its superiority in fostering economic growth.

Further, artificial intelligence facilitates the handling of large volumes of financial data, verifies its authenticity, and provides concise analyses that aid in the creation and application of successful economic strategies. By enhancing its technological sophistication, artificial intelligence can improve the effectiveness of the financial system and contribute to long-term economic growth (Batova et al., 2021; Tan, 2019). This might be advantageous for the advancement of the national economy.

According to the Ministry of Education's 2018 notice, "Action plan for AI innovation in colleges and universities," colleges and universities must "improve AI talents cultivation system" and "Enlarge the collaboration in innovation & strategic research for AI" (Kong & Feng, 2017). Manyika and Sneader (2018), estimate that between 2016 and 2030 automation may displace 400 million jobs, or around 15% of the world's employment. Therefore, attaining sustainable economic growth is currently the primary goal of policymaking. The average annual economic growth over the last three decades has been 3%, which is more than the size of the global economy during that time. Thus, there are notable differences between developed and developing countries. In this sense, using natural resources is crucial to achieving sustainable economic growth, and the impact of contemporary technologies on this usage is significant (Division, 2002). According to Acemoglu and Restrepo (2018), new tasks tend to increase the labor share and labor demand. In specific industries, automation results in employment losses, while in others, it leads to job growth (Bessen, 2017). Zinser et al. (2015), a global consulting organization, predicted that by 2025, the percentage of jobs performed by robots across all manufacturing sectors will rise by 15% (from an average of roughly 10% globally to about 25%). According to Acemoglu and Restrepo (2016), automation reduces employment, and the labor share in a static model in which capital is fixed, and technology is exogenous; however, the new tasks created by this automation raise labor demand.

In the AI era, we should concentrate on developing new-type engineering and technology talents with thinking, attitude, skills, and knowledge of innovation and entrepreneurship in order to promote the development of technology and economy in the country, given the strategic assumptions and choices made by the new technological revolution, new industry revolution, and new economic mode. Anonym (2015), ecosystem resources have historically received little attention in policymaking circles, even though they are essential to maintaining life and the economy. This is because they are difficult to assess. Recognizing that the loss of natural resources, such as the atmosphere's capacity to absorb carbon emissions, poses a significant threat to sustainable economic growth, there have been global efforts to integrate analyses that account for the significance of ecosystems in the creation and application of policies (Chukwu, 2020).

Long-term effects of AI are possible (though unstudied) because there are not enough reliable study techniques, even though existing scientific evidence disproves the technological determinism of such fake news (Petit, M. 2018). Therefore, a significant change is required to encourage collaboration and reduce the risk that AI will dictate citizen behavior. A multi-currency financial system that supports a circular economy is Finance 4.0 (Scholz et al., 2018; Hamid 2025). By 2015, Pakistan had placed a top priority on the implications and development of AI, progressively encouraging and advancing AI-related policies, offering nurturing resources, and obtaining dependable government support for AI system development. By including artificial intelligence in its fourteenth five-year framework, which outlines the use of AI for the nation's future growth and development, Pakistan has linked AI to the goal of anticipating economic growth.

Similarly, as resource and ecological pressures increase steadily and the labor supply of production factors declines, Pakistan's economic growth may be hindered by a heavy debt load. The rate of fixed investment may also decline because of issues such as the production capacity process and the blurring of the real estate system. Pakistan must adopt sustainable practices and reduce its reliance on traditional energy sources to achieve sustainable economic growth and development. In response, Pakistan's economic success has been enlightened by the disclosure of the A.I. system, and the country could fully use its artificial intelligence resources to achieve long-term economic progress (Romer, 1990). However, one of the most important issues for long-term economic development is the sustainable growth, progress, and exploitation of natural resources. The growth of natural resource development and utilization heightens concerns about human resource management. Natural resource management in Pakistan is associated with multiple sustainability challenges (Ziran, 1999).

Overall, there is a lack of literature that discusses how managing natural resources and artificial intelligence affect economic progress and prosperity. As a result, there is insufficient empirical support. Thus, there are both drawbacks and remedies. Still, the research now available supports the following: Handling natural resources with AI might be a more intelligent way to achieve sustainable growth, since AI could replace outdated production methods with the latest methods to enhance production and distribution systems. Thus, several studies detail how managing natural resources contributes to achieving the SDGs. However, no research has been conducted to jointly assess the contributions of resource management and AI to economic growth. The following study aims to close the gap by examining how natural resource management and artificial intelligence affect Pakistan's economic development and growth between 1990 and 2024. The following study's goals are to examine the role of artificial intelligence in fostering economic development and to assess the importance of managing natural resources for achieving long-term, stable economic growth. To evaluate the artificial intelligences is irregular effect on economic expansion. What recommendations for policy should be made in light of our findings?

LITERATURE REVIEW

The development of artificial intelligence, a significant factor propelling the upcoming wave of technical advancement and industrial growth, is the means of establishing cross-border consolidation, human-machine collaboration, data processing, and human sharing and cogeneration in an intelligent economic form. In contrast, artificial intelligence has played a crucial role in economic development through intelligent consolidation, digitalization, and the concept of innovative development. It has also improved the exchange model, increased distribution regulation, and reshaped the production model (Pradhan et al., 2020). Using annual data from 1991 to 2007, Guloglu and Tekin (2012) experimentally examined the causal relationships among R&D spending, innovation, and economic development across 13 high-income OECD economies. According to the VAR model's implications, the study found a positive correlation between technological advancements and economic growth, which is consistent with endogenous growth theory. In a similar vein, Zachariadis (2003) examined the relationship between technological advancement, research and development, and economic prosperity for the US economy from 1963 to 1998. The findings clarified the beneficial effect of development and research on economic prosperity. They noted that the intensity of R&D has a positive effect on the patenting ratio, whereby patenting boosts technological advancement, which, in turn, boosts productivity and, thus, economic growth.

Similarly, Liu & Xia (2018) examined the relationship between China's R&D spending, innovation, and economic growth from 1995 to 2016. They suggested that Investment in research and development (R&D) can drive technological innovation, a key factor in a nation's social advancement and sustained economic development. The study's conclusions revealed a long-term relationship among the three Series. They proposed that, to digitize the economy, there is an urgent need to increase funding for research and development. The concept of digital infrastructure, which inexorably connects industries, research, and academia by using data to facilitate the integration and advancement of the digital economy, is also a result of artificial intelligence, according to Xian (2023). According to this study, the increasing use of artificial intelligence technology has boosted the economy and has been heralded as the catalyst for the fourth industrial revolution.

Besides, database development reduces innovation costs, enhances innovation effectiveness, and eliminates the information gap between production and consumption. According to Chen, Y. B. et al. (2019), increasing worker productivity and promoting economic prosperity are the primary objectives of artificial intelligence research. By combining human and machine intelligence, artificial intelligence increases labor productivity, extends the labor pool, reduces human physical labor in production, and raises automation standards.

When employed, artificial intelligence improves product quality by altering the composition of production elements. AI is replacing simple labor in production, increasing demand for high-end labor, or human capital. Foremost, the development of AI technology requires the participation of elite talent; also, its implementation requires specialized personnel to oversee and maintain it. Compared to simple physical labor, human capital with specific abilities and expertise is a highly effective element in building superior value-added wealth (Kuo, Kai-Ming, 2019). Using data from the United States, Schmookler (1966) examined how innovation affects economic development and provided empirical support for demand-pull theory. The findings show that the rate of patent applications and production growth is most strongly correlated with capital market investment.

Further, Fan et al. (2017) planned a study for China to examine the relationship between economic welfare and innovation. The results indicate that elements of innovation, such as technical personnel and resources, have a significant impact on economic growth. Similarly, by simplifying complex phenomena and enabling technical improvements, artificial intelligence can boost innovation, according to Ryman-Tubb et al. (2018). Natural resources are essential for human survival and social advancement because they are a significant source of production and lifestyle choices. Because there are two primary avenues for development—natural resources and energy—the usage of resources increases as the social and economic system grows, especially in China. If used properly, natural resources can have a significant economic impact. Gylfason et al. (1999) highlighted the importance of natural resources in their study. They concluded that they could raise a country's currency value by increasing the export of raw materials from its abundance.

Regarding the relationship between the management of natural resources and economic growth and development, several studies offer varying conclusions. In a separate study, Li and Xiao (2019) empirically analysed the relationship between economic affluence and natural resource management in China from 2005 to 2016 using fixed-effect regressions and time-series analysis. The study's estimates show a positive link between resources and economic welfare: natural and water resources positively influence economic development, while forest resources negatively affect it. Papyrakis and Gerlagh (2004) identified two types of link between natural resource management and economic development, each with both positive and negative consequences. It is argued that the resource curse phenomenon is valid only when adverse effects outweigh positive ones.

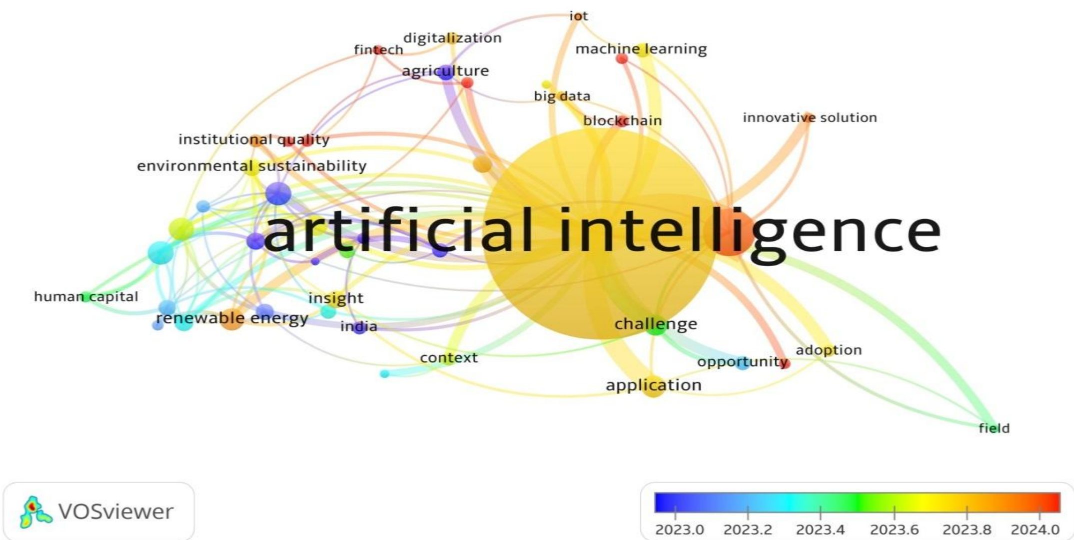

Figure 1: AI and Economics Growth importance in current decade

Also, natural resources may negatively affect economic growth, according to Bravo-Ortega & De Gregorio (2007). They showed that natural resources have a favorable effect on income in nations with low human capital by employing the fixed effect technique between 1970 and 1990. Similarly, using random- and fixed-effects models, Coulibaly (2013) investigated the relationship between economic development and the use of natural resources in African states between 1980 and 2012 and found a favorable long-term association. However, because each country's anomalies show different links between economic growth and innovation, the results varied across countries. Since the results may aid in shaping policies related to China's diversification goal, it is vital to reevaluate the relationship between artificial intelligence and economic development, as well as China's natural resource management, given the indeterminate findings.

THEORETICAL FRAMEWORK

A theoretical framework is developed to investigate the relationships among artificial intelligence, natural resource management, and Pakistan's economic affluence and development, while accounting for existing research. Several studies examined the effects of A.I. and natural resource management across various countries, but none analyzed both in the same survey. Many researchers have employed different estimation techniques to examine the desired relationship.

Several economic theories explain the importance of innovation and technological advancement in promoting economic growth, and the neoclassical Solow growth model posits that technology is a dominant factor in economic affluence and development. Again, innovation and knowledge expansion are more important for economic advancement than any element of production, according to endogenous technological growth. As a result, people have begun to take notice of the internal forces driving economic growth through innovation and technological advancement (Romer, 1990; Solow, 1957).

Likewise, multiple studies have addressed the significance of natural resources. If properly managed and used, nations with abundant natural resources experience greater growth and development. Economic development and the management of natural resources are positively correlated (Boianovsky, 2018; Auty, 1994; Brunnschweiler, 2008).

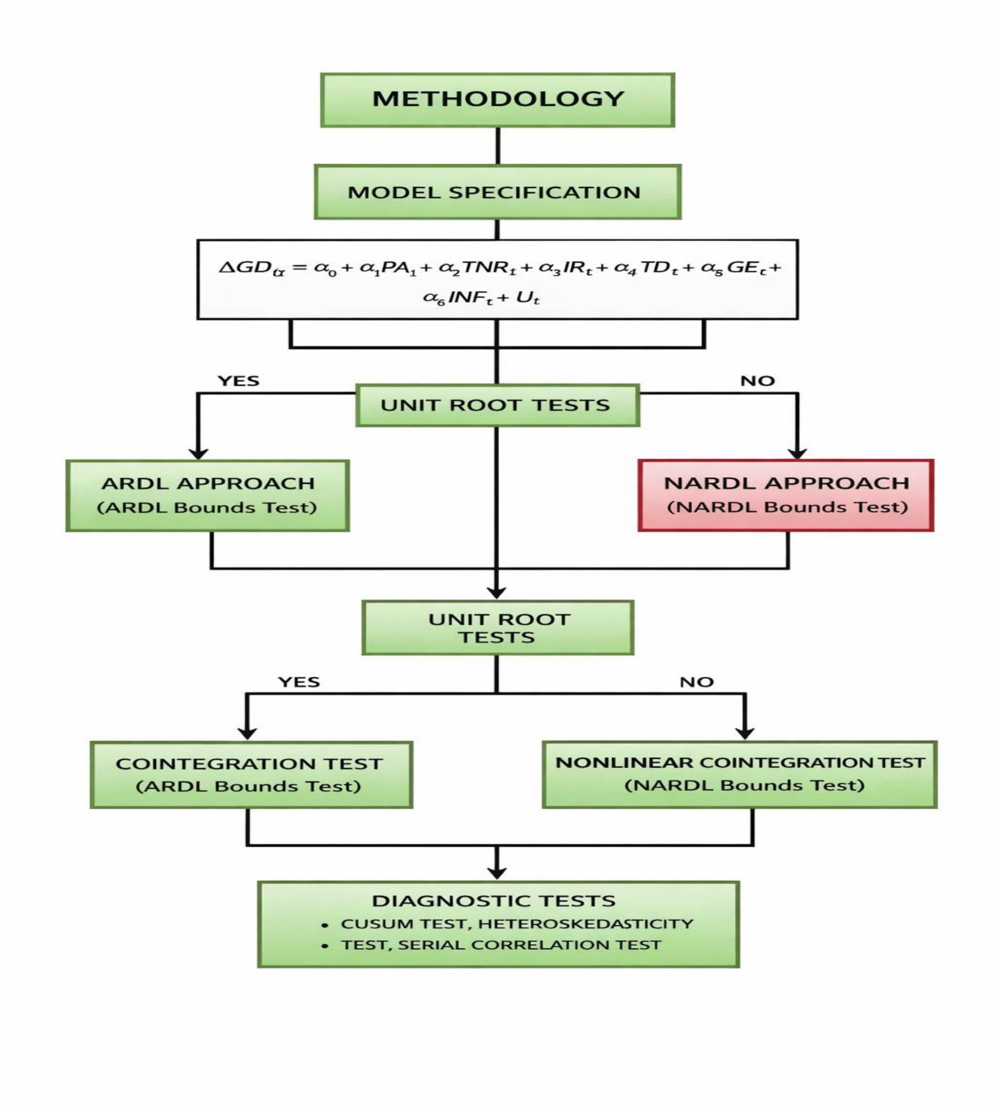

Figure*: 2 *Flowchart of the Study

METHODOLOGY

Model description

Regarding the literature mentioned, the empirical model used to assess the impact of artificial intelligence and the management of natural resources on Pakistan's economic growth between 1990 and 2024 is detailed below.

$$GDP_t = \alpha_0 + \alpha_1 PA_t + \alpha_2 TNR_t + \alpha_3 IR_t + \alpha_4 TD_t + \alpha_5 GE_t + \alpha_6 INF_t + U_t \quad \text{eq...1}$$

Here PA patent applications are used to assess AI's influence, following Link (2021), to comprehend how technology transfers, affect enterprises, according to several scholars, like Bond and Malik (2009) and Bravo-Ortega and De Gregorio (2007), who investigated the role of natural resources in economic management, TNR (total natural resource rent) is used to analyses the impact of natural resource management on economic advancement. Inflation (INF), trade and development (TD), interest rates (IR), and research and development (RD) are additional explanatory variables used to assess their influence on economic growth and development.

Estimation Technique

Data from the World Development Indicators 2024 are used in this analysis, which uses annual time series for Pakistan from 1990 to 2024. To estimate the relationship between artificial intelligence and the available studies, several techniques have been used. The ARDL technique is the most reliable and widely used approach for examining the long-term relationship between the variables. Apart from this, it doesn't account for the nonlinearity in the relationships among the variables being studied. Moreover, in identifying lower and upper dimensions, bound testing is implied to confirm the model's stability.

Table: 1 Description of the variables.

Variable		Unit	Description
Gross Domestic Product	GDP	Constant 2015 US$	GDP at consumer's price is the aggregate of total value added by all domestic producers, including product taxes subtracted subsidies not in product. Data is based on constant prices and expressed in U.S. dollars.
Patent Applications	PA	Numeral	Patent applications are global requisitions applied via licensed treaty cooperation, a treaty for rights to invent. Patent refers to the process of producing something new and technical assistance to economic problems and securing innovation for 20 years.
Total Natural Resources Rent	TNR	% of GDP	It comprises rents from all sources, including forest rents, oil, mineral, coal & natural gas rents.
Interest Rate	IR	% of GDP	It is the lending rate adjusted for inflation measured as the GDP

			deflator.
Trade and Development	TD	% of GDP	Trade is the aggregate of imports (x) and exports (m) of services and goods expressed as a percentage of GDP.
Government Expenditures	GE	% of GDP	Total government expenses on all goods and services.
Inflation	INF	% of GDP	It is measured as CPI shows an annual % change in price consumers required to buy a basket of commodities, fixed or may vary annually. Laspeyre's formula is mostly implied.

$$LGDP_t = \alpha_0 + \alpha_1^+ LPA_t^+ + \alpha_2^+ LPA_t^- + \alpha_3 LTNR_t + \alpha_4 LIR_t + \alpha_5 LTD_t + \alpha_6 LGE_t + \alpha_7 LINF_t + U_t \quad eq.......2$$

The fragmented positive and negative components of the focused variables are added to equation (1). The parameters are indicated as follows:

The components α_0, α_1^+, α_2^+, α_3, α_4, α_5, α_6, and α_7 collectively form the set α. The vector of undetermined long-run parameters for artificial intelligence (denoted as LPA_t) is composed of LPA_O, LPA^+_t, and LPA^-_t. Here, LPA^+_t and LPA^-_t represent the partial aggregates of the positive and negative varying constituents within LPA_t, respectively.

$$LPA_t^+ = \sum_{k=1}^{t} \Delta LPA_j^+ = \sum_{k=1}^{t} \max(\Delta LPA_j, O), LPA_j^- = \sum_{k=1}^{t} \Delta LPA_j^- = \sum_{k=1}^{t} \min(\Delta LPA_j, O) \quad eq.........3$$

Equations (3) and (4) represent the positive and negative fragmented aggregate decomposition of artificial intelligence (AI), respectively, to analyze the asymmetric influence of LPA on economic growth and development.

Unit root test

Understanding the stationarity and non-stationarity of time series data is essential for research. When a series's mean and variance remain constant, it is said to be stationary (Ikram & Gul, 2024). Besides, a stationary series has continuous shocks that dominate periodic gaps, whereas a non-stationary series does not. In a non-stationary series, a unit root is present, leading to inaccurate results. To account for serial correlation, the Phillips-Perron test suggests using Newey-West standard errors. We'll use a five percent significance level. The t-statistics for the measures must exceed the 5% critical value. Thus, to be sure that a series has a unit root, the probability value must be less than 0.05. Besides, the Philips Perron test equation is as follows:

$$yt = ayt - 1 + wt$$

Long-run cointegration shows a long-run association among the variables (Ullah et al., 2023). In economics, various econometric methods are commonly used to test for the long-run association, such as Johansen Cointegration (JJ), VECM, and so on (Gul et al., 2023). The most commonly used approach is the ARDL bounds test, which determines whether a set of variables is cointegrated. It is designed to test the existence of cointegration variables. This method is mainly practical because it can be used when the variables are integrated of mixed order [I (0) and I (1)]. The method is not valid if any variable is integrated of order I (2). The ARDL approach is estimated using OLS (simple regression) (Jamal et al., 2024) and includes lagged values of both the input and output variables. Post-estimation, cointegration is tested using the bounds test by comparing the F-statistic to the critical values. If the computed F-statistics > upper bound I (1), it means no cointegration exists, and a lower value means cointegration exists (Khan et al., 2023; Khan et al., 2023). Following the process proposed by Shin et al. (2014a), the empirical framework employs the Autoregressive Distributed Lag (ARDL) model, expressed as:

$$\Delta LGDP_t = e_0 + \varepsilon_1 LGDP_{t-1} + \varepsilon_2^{+} LPA_{t-1}^{+} + \varepsilon_3^{+} LPA_{t-1}^{-} + \in_4 LTNR_{t-1} + \in_5 LINR_{t-1} + \in_6 LGE_{t-1} + \in_7 LTD_{t-1} + \in_8 LINF_{t-1} + \sum_{i=0}^{a} (\emptyset_i^{+}\, \Delta LPA_{t-i}^{+} + \emptyset_i^{-} \Delta LPA_{t-i}^{-}) + \sum_{i=0}^{a} (\emptyset_i^{+}\, \Delta LTNR_{t-i}) \sum_{i=1}^{k} (\varphi_i\, \Delta LIR_{t-i}) + \sum_{i=0}^{n} \rho_i\, \Delta IGE_{t-i} + \sum_{i=1}^{n} \rho_i\, \Delta LGE_{t-i} + \sum_{i=1}^{n} \rho_i\, \Delta LINF_{t-i} + U_t \qquad eq\text{.........} 4$$

Here, $p, a, k, n, p, a, k, np, a, k, n$ denote the lag orders. It is assumed that equation (5) may involve hidden cointegration, as indicated in equation (4). Consequently, the precise interpretation of the asymmetric components might be challenging. To address this issue, the condition $\alpha_1^{+} = -\epsilon_2 + /\epsilon_1$is applied to the values in equation (4). The short-term impact of increased AI usage on economic growth and development is measured by ∑i=0 nϕ_i^{+} , while the minimal use of AI is assessed through ∑i=0 nϕ_i^{-} . Both the short-term and long-term effects of AI on economic progress are captured by the application of equation (4). Therefore, all Series must be stationary in order to apply ARDL (Gul et al., 2023; Gul & Khan 2021). To verify the stationary of the data used, various tests are available. The following is one of the often used tests to verify stationarity, according to Phillips and Perron (1988).

RESULTS AND DISCUSSIONS

The study's findings and results are presented in this section. The findings are described as follows:

Table.2 Unit Root Test.

Variable	I(0)	I(1)
GDP	-1.0024	-4.3618
PA	2.7305	-4.5481
IR	-5.6265	-6.5932
INF	-0.46211	-4.6487
GE	-1.8634	-6.2483
TNRR	-1.7050	-5.2435
TD	-1.9838	-5.6667

The ADF (Dickey-Fuller) test was initially used to determine whether the data were stationary. However, it failed to meet the requirements, as it treated some variables as first-differenced and others as second-differenced. Because the Phillips-Perron test makes all variables stationary at the initial difference needed to apply our chosen estimation method, it has been used to determine whether the data are stationary. The GDP, patent applications, interest rates, natural resource rent, inflation, trade, and government spending are all non-stationary at level I (0), according to the P.P. test results. At the first difference, however, they become stationary (see Table 2).

Table 3 Descriptive Statistics

	GDP	PA	IR	INF	G.E	TNRR	TD
Mean	11.3352	145.911	10.8242	9.47565	105.7179	1.73675	30.6815
Median	11.3587	94.0000	8.93744	9.27976	106.3067	1.63959	31.1046
Maximum	11.6023	600.000	68.0104	30.7681	111.9502	2.89116	38.4993
Minimum	11.0431	16.0000	0.92216	2.52932	100.3209	0.96533	21.4599
Std. Dev.	0.17260	147.4795	11.1241	5.71064	3.20625	0.56701	4.72821

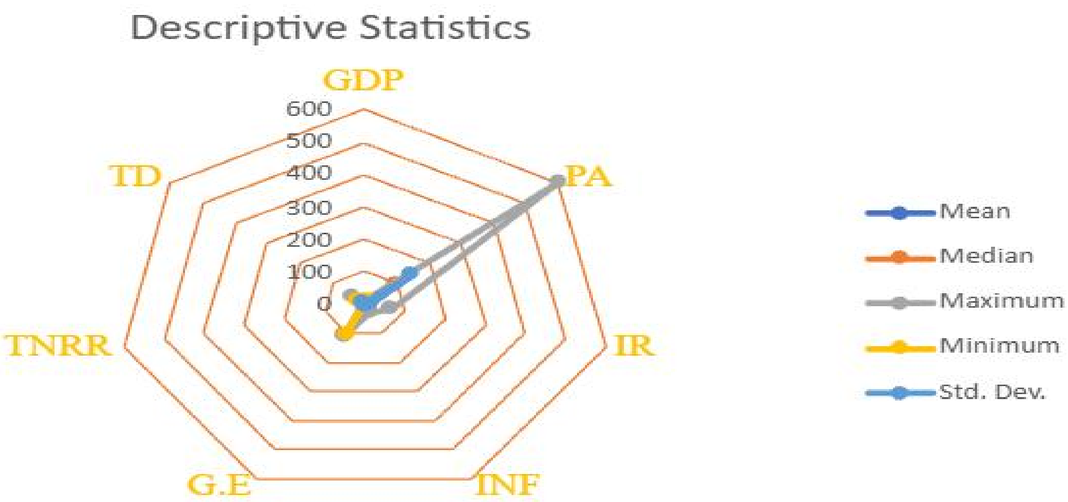

***Figure* 3.** *Spider diagram of summary statistics*

Table 3 provides the descriptive statistics for the variables used in the study: GDP, PA (Public Administration), IR (Interest Rate), INF (Inflation), G.E (Government Expenditure), TNRR (Total Natural Resource Rents), and TD (Trade). The mean and median values for each variable highlight the central tendency, with GDP having a mean of 11.3352 and a median of 11.3587, suggesting a relatively stable distribution. The maximum and minimum values reveal the range of variability, such as PA spanning from 16.0000 to 600.000, and IR ranging from 0.92216 to 68.0104. Standard deviations reveal the degree of dispersion, with PA showing the highest variability (Std. Dev. = 147.4795) and GDP the lowest (Std. Dev. = 0.17260). These statistics provide an outline of the data's distribution, variability, and central tendency, which are critical for understanding the dynamics of the variables in the analysis. Figure 3 shows a spider diagram of our descriptive statistics.

The different colors show the mean, median, minimum, maximum, and standard deviation of our indicator, while Figure 4 illustrates these relationships through a heat plot of the correlation matrix.

Table 4 Correlation

	GDP	PA	IR	INF	GE	TNR	TD
GDP	1						
PA	0.7905	1					
IR	0.0846	0.0409	1				
INF	0.2125	0.5132	0.2204	1			
GE	0.7662	0.6979	0.1188	0.3880	1		
TNR	0.0541	0.1297	0.0274	0.0556	0.00626	1	
TD	0.4689	0.2961	0.1542	0.4148	0.0288	0.1553	1

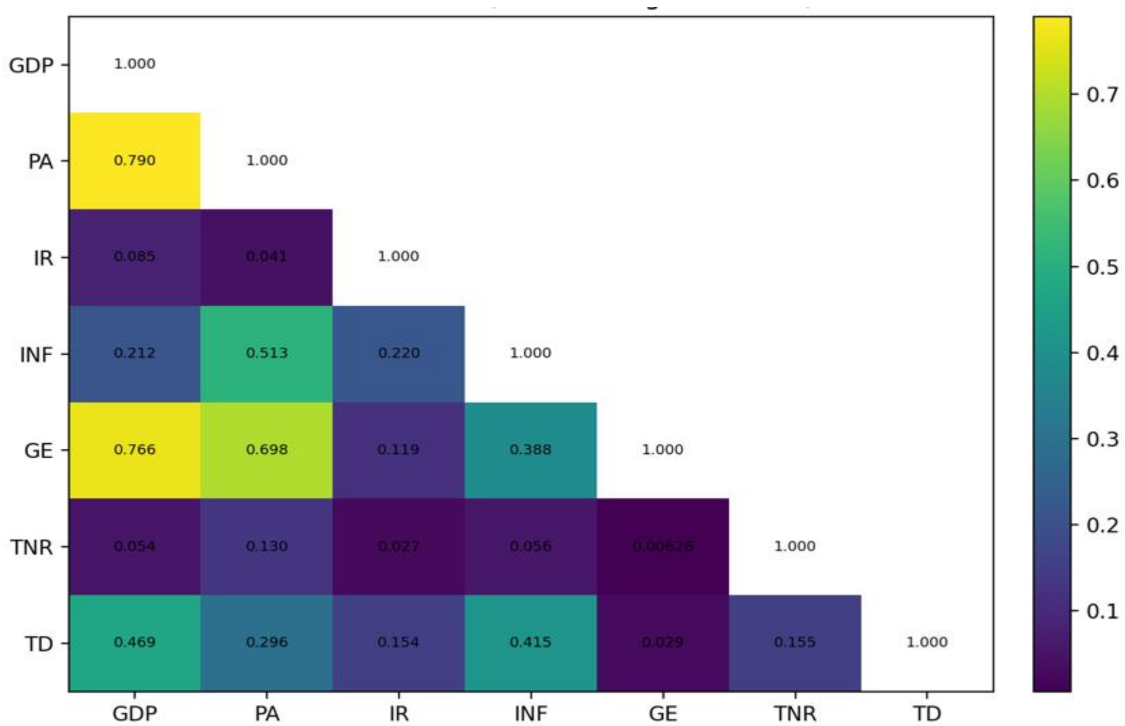

Figure*: 4 *Heat Map of correlation matrix

Table 4 presents the correlation matrix among the variables: GDP, PA (Public Administration), IR (Interest Rate), INF (Inflation), GE (Government Expenditure), TNR (Total Natural Resource Rents), and TD (Total Debt). The results show that GDP has a strong positive correlation with PA (0.8505) and GE (0.7662), suggesting that public administration and government expenditure are closely associated with economic performance. Moderate correlations are observed between GDP and TD (0.4689) and between INF and PA (0.5132). Other variables, such as TNR, show weak correlations with most variables, suggesting limited direct relationships in the dataset. The matrix highlights key relationships while suggesting minimal

Multicollinearity concerns, as most correlations fall below critical thresholds for Multicollinearity. This analysis helps identify significant variable associations for further modeling and interpretation.

Table 5 Results of the Cointegration test

Bound test (ARDL)			
Test, (K)	**Estimate**	**Lower bound (0)**	**Upper bound (1)**
F-stat, (6)	3.62	2.45	3.61

Table 5 presents the results of a co-integration test using the Bounds Testing approach within an ARDL framework. The F-statistic value is 3.62, which is compared against the critical lower bound (2.45) and upper bound (3.61) at the chosen significance level. Since the F-statistic equals the upper bound, the test indicates the presence of marginal evidence for a long-run relationship (co-integration) among the variables. This suggests that further analysis or confirmation may be required to establish a definitive conclusion about co-integration in the model.

Table 6 ARDL Results

(Panel A) SHORT-RUN STATISTICS				
Variable	Coefficient	S.E	t-stats	P value
D(PATENT)	0.000077	0.000031	2.512585	0.0188
D(TNR)	0.007406	0.003178	2.330232	0.0282
D(INTEREST)	-0.000083	0.000151	-0.553396	0.5849
D(INFLA)	-0.001409	0.000537	-2.624421	0.0146
D(GOVEXP)	0.001350	0.001043	1.294486	0.2073
D(TRADE)	0.000094	0.000685	0.136442	0.8926
Coint.Eq(-1)	-0.078588	0.031022	-2.533255	0.0179
(Panel-b) LONG RUN ESTIMATES				
Variable	Coefficient	Std. Error	t-statistics	Prob
PATENT	0.000985	0.000359	2.743391	0.0111
TNR	0.094243	0.045843	2.055755	0.0504
INTEREST	-0.001061	0.001852	-0.573090	0.5717
INFLA	-0.017926	0.009159	-1.957181	0.0616
GOVEXP	0.017182	0.009518	1.805148	0.0831
TRADE	0.001190	0.008936	0.133144	0.8951
C	9.561538	0.875868	10.916643	0.0000

Table 6 presents the ARDL model results, divided into short-run and long-run estimates. In the short run (Panel A), significant positive impacts on the dependent variable are observed for changes in PATENT ($p = 0.0188$) and TNR ($p = 0.0282$), while INFLA exerts a significant negative effect ($p = 0.0146$). The error correction term (Coint.Eq (-1)) is significant ($p = 0.0179$) with a negative coefficient, confirming the presence of a stable long-run relationship and indicating that approximately 7.86% of deviations from the equilibrium are corrected each period. In the long run (Panel B), PATENT and TNR have significant positive coefficients (p = 0.0111 and p = 0.0504, respectively), while INFLA shows a near-significant negative effect (p = 0.0616). Other variables, including INTEREST, GOVEXP, and TRADE, are not statistically significant in either time frame. The constant term (C) is highly significant (p = 0.0000), underscoring its importance in the model. These findings provide insights into both the immediate and enduring effects of the variables under investigation.

Diagnostic Tests Results

Table 7 Diagnostic tests

Diagnostic	F-Statistic	P-value
Heteroscedasticity (ARCH-test)	**1.176**	**0.350**
Serial Correlation (L.M. test)	**0.809**	**0.457**

Table 7 presents the diagnostic test results for the ARDL model to ensure its robustness and validity. The Heteroscedasticity test (ARCH test) yields an F-statistic of 1.176 with a p-value of 0.350, indicating no evidence of Heteroscedasticity in the model. Similarly, the serial correlation test (L.M. test) shows an F-statistic of 0.809 with a p-value of 0.457, confirming the absence of serial correlation in the residuals. These results suggest that the model is well-specified and that its estimates are reliable for inference and interpretation.

STABILITY TEST (CUSUM & CUSUM^2)

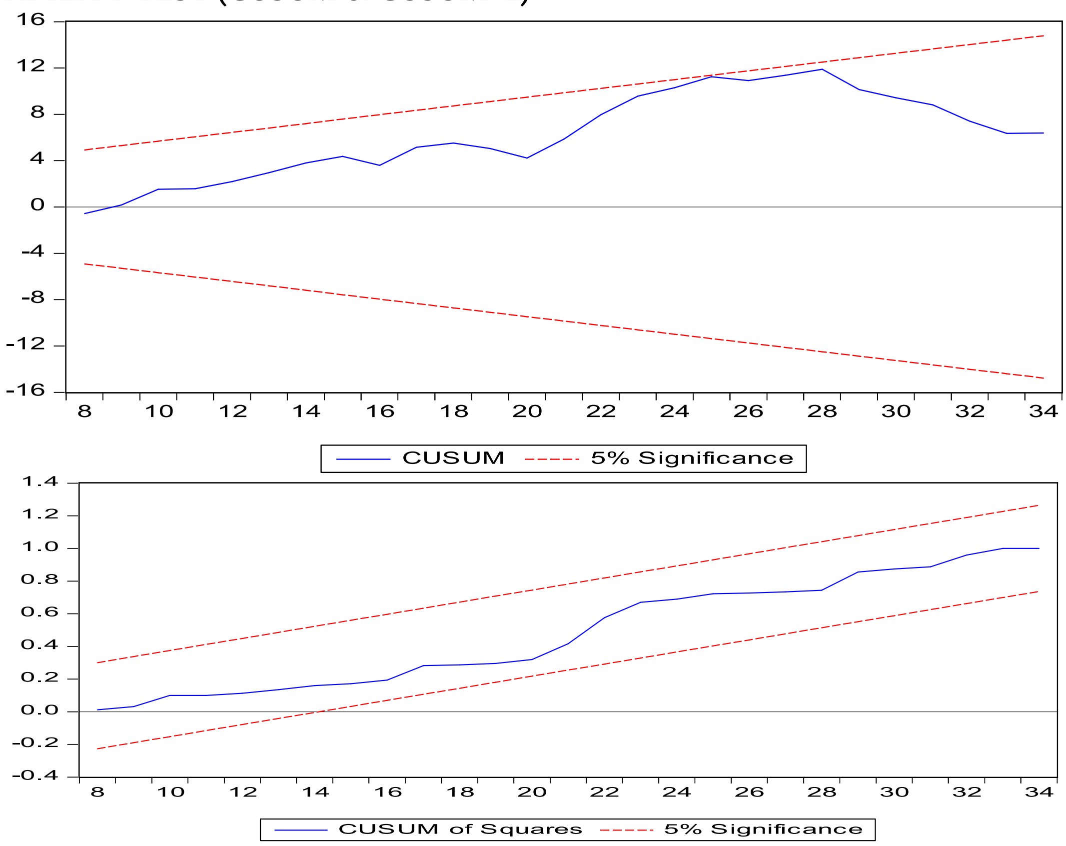

***Fig*1 & 2 *CUSUM* & *CUSUM*^2**

The graph shows the CUSUM & CUSUM^2 test for model stability, with the blue line representing the cumulative sum of squared recursive residuals and the red dashed lines indicating the 5% significance bounds. Throughout the observation period, the CUSUM of Squares line remains within the critical boundaries, signifying the absence of structural instability in the model. This confirms that the model's variance is stable over time, enhancing the reliability of its parameter estimates and its ability to predict relationships among the analyzed variables.

CONCLUSION AND POLICY RECOMMENDATIONS

The study explores the impact of artificial intelligence (AI), as measured through patent applications, and natural resource management on Pakistan's economic growth from 1990 to 2024. The ARDL process provides insights into the asymmetric long-term and short-term relationships between the variables. The results reveal that patent applications and total natural resource rents positively influence GDP in both the short- and long-run, underscoring the importance of AI innovation and resource management. Conversely, inflation negatively affects economic growth. Other factors, such as government expenditure, trade, and interest rates, exhibit mixed or insignificant effects. The diagnostic tests confirm the model's robustness and stability, ensuring reliable conclusions. These findings emphasize the role of technology and resource efficiency in fostering sustainable economic development. The study's results suggest significant recommendations, such as first, the strong positive relationship between patent applications and economic growth underscores the need for policies that foster AI innovation. The government should increase investments in research and development (R&D) and establish partnerships between public institutions and private industries. Secondly, in Pakistan, to reduce the share of natural resource rents in GDP, the country should develop policies that ensure the efficient and sustainable use of natural resources.

REFERENCES

Acemoglu, D., & Restrepo, P. (2016). *The race between machine and man: Implications of technology for growth, factor shares and employment* (No. w22252). National Bureau of Economic Research.

Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation, and work. In *The economics of artificial intelligence: An agenda* (pp. 197-236). University of Chicago Press.

Ansari, U., Naz, F., Husain, S. S., Shabbir, T., ul Hasnain, S. M., Memon, S., ... & Nazish, S. A. (2020). Effects of Social Media Group Communication Campaigns among School Children: An Experimental Study. *Ilkogretim Online*, *19*(1), 686-699.

Anonym (2015). Interpretation to Li Keqiang's Call of "Mass Entrepreneurship and In-novation": "Mass" Is the Key Word. Economic Daily

Aurangzeb, M., Uddin, S. S., Aziz, Z., & Bibi, S. (2025). Great Power Rivalry and the Shifting World Order Since 2001: A Realist Study of US-China

Competition. *Journal of Political Stability Archive*, *3*(3), 1601-1611.

Batova, M., Baranov, V., & Mayorov, S. (2021). Automation of economic activity management of high-tech structures of innovation-oriented clusters. *Journal of Industrial Integration and Management*, *6*(01), 15-30.

Bessen, J. (2019). Automation and jobs: When technology boosts employment. *Economic Policy*, *34*(100), 589-626.

Bond, S.R., Malik, A., 2009. Natural resources, export structure, and investment. Oxf. Econ. Pap. 61 (4), 675–702.

Bravo-Ortega, C., De Gregorio, J., 2007. The relative richness of the poor? Natural resources, human capital, and economic growth. Lederman Maloney 71–103.

Chen, Y. B., Lin, C., & Chen, X. L. (2019). Artificial intelligence, aging and economic growth. *Economic Research Journal*, *54*(07), 47-63.

Chukwu, V. E. (2020). Potentials, drivers and barriers to green economy transition: Implications for Africa. *Advanced Journal of Plant Biology*, *1*(1), 7-17.

Coulibaly, I., 2013. Long Term Economic Impact of the Natural Resources and Human Capital on the Growth Rate. Research Papers. Paper, p. 399.

Gul, A., & Khan, A. W. (2021). The Effect of Small-Scale Industries on Employment Level in Pakistan. *Journal of Research and Reviews in Social Sciences Pakistan*, *4*(2), 1393-1404.

Gul, A., Khan, S. U., & Abbasi, R. A. (2023). Vicious Circle of Health Expenditure: Time Series Evidence from Pakistan. *Journal of Contemporary Macroeconomic Issues*, *4*(1).

Gul, A., Sadiq, S., & Khan, S. U. (2023). Conflicts and The Structure of Economy: A Case of Trade in Pakistan. *Journal of Development and Social Sciences*, *4*(4), 23-42.

Guloglu, B., & Tekin, R. B. (2012). A panel causality analysis of the relationship among research and development, innovation, and economic growth in high-income OECD countries. *Eurasian Economic Review*, *2*, 32-47.

Gylfason, T., Herbertsson, T.T., Zoega, G., 1999. A mixed blessing: natural resources and economic growth. Macroecon. Dyn. 3 (2), 204–225. He, Y., 2019.

Hamid, S. (2025). The Reforming Pakistan's Education System: Bridging the Gap for 21st-Century Skills : Reforming Pakistan's Education System: Bridging the Gap for 21st-Century Skills. *Dialogue Social Science Review (DSSR)*, *3*(3), 637–647. https://thedssr.com/index.php/2/article/view/391

Hamid, S., & Abbas, S. (2025). Artificial intelligence as a pedagogical scaffold in K–12 language and literacy education. Annals of Human and Social Sciences, 6(4), 41–56.

Hussain, N., Javed, B., & Sarmad, M. (2019). Corporate social responsibility and investor's intention to invest: analyzing the role of corporate identity and corporate image. *Pakistan Journal of Commerce and Social Sciences (PJCSS)*, *13*(1), 150-164.

Ikram, N., & Gul, A. (2024). The Impact of Conflicts On Trade: A Case Study Of Pakistan And India. *Kurdish Studies*, *12*(4), 1307-1316.

Jamal, F., Zhijun, Y., Khan, U. U., Zubair, M., Ahmad, S., Sultan, F., & Ullah, I. (2024). The impact of finance, infrastructure and training on the performance of SMEs in Pakistan. *South Asian J Soc Stud Econ*, *21*(4), 4.

Khan, H. U., Khan, S. U., & Gul, A. (2023). The Dance of Debt and Growth in South Asian Economies: Panel ARDL and NARDL Evidence. *Qlantic Journal of Social Sciences*, *4*(3), 112-123.

Khan, U. S., Khan, Z. M., & Gul, A. (2023). Democracy's Role in Shaping Pakistan's Economic Growth: An Empirical Evidence from Pakistan. *International Journal of Contemporary issues in social sciences*, *2*(3), 356-367.

Kong, L. Q., & Feng, Y. (2017). Development Difficulties and Transformation of Paths of Entrepreneurship Education for College and University Students in the Period of New Normal. *Education and Vocation*, *15*, 66-71.

Kuo, Kai-Ming. (2019) Artificial intelligence development, industrial structure transformation and upgrading and labor income share changes[J]. Management World, (7): 60-77

Li, J., Xiao, D., 2019. Natural resources and economic development in the Western Regions of China. In: IOP Conference Series: Earth and Environmental Science, Link, A. N. Technology Transfer at U.S. Federal Laboratories: R&D Disclosures Patent Applications. Technology Transfer and Entrepreneurial Innovations: Policies Across Continents, pp. 45–58, 2021.

Liu, C., & Xia, G. (2018). Research on the dynamic interrelationship among R&D investment, technological innovation, and economic growth in China. *Sustainability*, *10*(11), 4260.

Maksanova, L. B. Z., Kharitonova, O. B., & Andreeva, A. M. (2021, October). Creating models of integrated development of ecotourism in Russian protected areas. In *IOP Conference Series: Earth and Environmental Science* (Vol. 885, No. 1, p. 012056). IOP Publishing.

Manyika, J., & Sneader, K. (2018). AI, automation, and the future of work: Ten things to solve for.

Papyrakis, E., Gerlagh, R., 2004. The resource curse hypothesis and its transmission channels. J. Comp. Econ. 32 (1), 181–193.

Petit, M. (2018). Towards a critique of algorithmic reason. A state-of-the-art review of artificial intelligence, its influence on politics and its regulation. *Quaderns del CAC*, *44*.

Phillips, P.C., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75 (2), 335–346.

Pradhan, R. P., Arvin, M. B., Nair, M., & Bennett, S. E. (2020). The dynamics among entrepreneurship, innovation, and economic growth in the Eurozone countries. *Journal of Policy Modeling*, *42*(5), 1106-1122.

Rabbani, S., Sarmad, M., Khattak, A., & Khan, M. (2020). Creative self-efficacy and product innovation: Uncovering the role of creativity and entrepreneurial passion. *International Journal of Innovation, Creativity and Change*, *13*(10), 901-924.

Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy*, *98*(5, Part 2), S71-S102.

Sarmad, M., Iqbal, R., Ali, M. A., & ul Haq, A. (2018). Unlocking spirituality at workplace through islamic work ethics: Analyzing employees' performance in islamic banks. *Journal of Islamic Business and Management (JIBM)*, *8*(2).

Scholz, R. W., Bartelsman, E. J., Diefenbach, S., Franke, L., Grunwald, A., Helbing, D., ... & Viale Pereira, G. (2018). Unintended side effects of the digital transition: European scientists' messages from a proposition-based expert round table. *Sustainability*, *10*(6), 2001.

Shin, Y., Yu, B., Greenwood-Nimmo, M., 2014b. Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. Festschrift in honor of Peter Schmidt: Econom. Method. Appl. 281–314.

Tan, M. J. (2019). Research on driving mechanism of transaction cost, convergence income and integrated development of three industries in rural areas promoting rural vitalisation.

Ullah, I., Nosheen, M., Shah, K. R., & Ahmad, N. (2023). Nexus between economic growth, energy consumption and environmental degradation: empirical evidence from economic cooperation organization countries. *PAKISTAN ISLAMICUS (An International Journal of Islamic & Social Sciences)*, *3*(2), 310-334.

United Nations. Population Division. (2002). *World population prospects: the 2002 revision: highlights*. UN.

Xian, F. (2023, March). Quantifying the Economic Benefits of Artificial Intelligence Technology. In *Proceedings of the 4th Management Science Informatization and Economic Innovation Development Conference, MSIEID 2022, December 9-11, 2022, Chongqing, China*.

Zachariadis, M. (2003). R&D, innovation, and technological progress: a test of the Schumpeterian framework without scale effects. *Canadian Journal of Economics/Revue canadienned'économique*, *36*(3), 566-586.

Ziran, Z. (1999). Natural resources planning, management, and sustainable use in China. *Resources Policy*, *25*(4), 211-220.