Artificial Intelligence, Human Capital Development And Economic Performance In Saudi Arabia (1990-2019)

Ismail Bengana[1*] , Bosede Ngozi Adeleye[2] , Bosede Ngozi Adeleye[2] , Kamel Si Mohammed[3] , Eltahir Ibrahim Elnour Salim[4] , Yahdih Semlali[5] , Musaddag Elrayah[6]

[1]Department of Quantitative Methods, College of Business, King Faisal University, Saudi Arabia
Department of economic sciences, College of Business and Economics, Ouargla University, Algeria
Email: ibenggana@kfu.edu.sa,
ORCID: 0000-0002-9968-4240
[2]Department of Accountancy, Finance, and Economics, Lincoln International Business School, University of Lincoln, United Kingdom
Email: NAdeleye@lincoln.ac.uk,
ORCID: 0000-0002-1274-714X
[3]Faculty of Economics and Management, University of Ain Temouchent, Algeria
Email: kamel.simohammed@univ-temouchent.edu.dz
[4]Department of Quantitative Methods, College of Business, King Faisal University, Saudi Arabia
Email: esalim@kfu.edu.sa
[5]Department of Management, School of Business, King Faisal University, Saudi Arabia,
Email: ysemlali@kfu.edu.sa,
ORCID:0000-0001-7886-128X
[6]Department of Management, School of Business, King Faisal University, Saudi Arabia,
Email: melrayah@kfu.edu.sa,
ORCID: 0000-0002-1802-150X
*Corresponding Author:
melrayah@kfu.edu.sa, ORCID: 0000-0002-1802-150X

Abstract

Human capital development and artificial intelligence (AI) are two interconnected concepts that are rapidility gaining traction globally. Thus, this study further examines the relationship between human capital (HC) and economic performance (GDP) using the Artificial Neural Network (ANN) methods to forecast how the GDP would respond to human capital development in

Saudi Arabia in the context of Vision 2030. From our findings, GDP plays a major part in establishing a reliable examination with anticipated human capital growth. These results have significant consequences, including comparing the better predictive accuracy of artificial neural network (ANN) studies versus conventional models. Finally, this study offers worldwide policymakers, decision-makers, and company executives insights.

Keywords: Human capital; Economic Growth; Artificial Intelligence; Saudi Arabia.

1 Introduction:

Investment in human capital development has become more critical in the contemporary knowledge-based economy in companies recognizing the worth of skills and knowledge as competitive advantages. Indeed, The relationship between human capital development and economic performance is also important because a more competent and informed workforce can contribute to improved output, higher levels of creativity, and, eventually, greater economic growth (Bonnet et al., 2022). Additionally, developing human capital can improve the general socioeconomic situation. When educated and skilled, people can improve the economy, increasing economic development and decreasing poverty and crime rates (Anser et al., 2020; Lochner, 2004). Furthermore, human capital affects economic growth through school enrollment, life span, birth, and death rates. human capital, including education and health, affects birth and death rates, which boosts economic growth(Goldin, 2016; Mousavi & Edmund Clark, 2021).

On the other side, Vision 2030 in Saudi Arabic is a complete strategy for societal change that was unveiled as a national project in 2016. The goal for Saudi Arabia in the ensuing decades is healthy economic and societal growth (Rexhepi, 2019). The three major vectors on which the strategy is centered are economics, community, and administration. It aims to improve living standards, expand and grow the Saudi economy, and strengthen openness, responsibility, and good administration. Vision 2030 in Saudi Arabia strongly emphasizes the human capital development, which is essential to accomplishing economic diversity, societal advancement, and sustainable progress.

This study employs two widely used metrics of human capital development to assess the effects of the United Nations Sustainable Development Goal 4 (UNESCO, 2019), which relates to human development, on economic progress in Saudi Arabia. The first indicator is enrollment in schools, essential for producing the trained workforce required for success and economic development. The second indicator of a health state is life expectancy at birth, which shows the well-being of the labor force. This research uses school enrollment and life expectancy at birth as measures for human capital development to guarantee that the analysis correctly reflects the input of human capital to economic growth and to prevent missing variable bias. The research uses these two metrics to offer a more thorough evaluation of the effect of human capital on Arabic Saudi economic development. This study also aims to prove the connection between human capital development and economic progress in Saudi Arabia using Artificial intelligence. This method seeks to cover a void in the literature on the effect of human capital development on economic progress in Saudi Arabia, which, to the author's knowledge, has not been thoroughly addressed. This research uses Artificial Neural networks (ANN) to provide a more solid examination of the connection between human capital development and economic progress in Saudi Arabia. The novel method provides factual data to guide policy choices and add to the current debate in Saudi Arabia about the significance of human capital development for economic progress. This study differs from existing research by investing in the relationship between GDP and human capital in light of vision 2030 in Saudi Arabic, whereas the period study ignored this vision. Since the human capital index quantitatively measures the present effects of health and education policies on future outputs, education levels are only roughly accurate. The Kingdom of Saudi Arabia's 2030 plan seeks to accomplish this. It focuses on creating a strategy based on the long-term growth of human capacities and their expansion to keep up with upcoming challenges. It is moving toward technology and artificial intelligence to achieve pedagogical excellence without boundaries. The rest of the paper is structured as follows: section 2 reviews the extant literature. Section 3 details the data and empirical model. Section 4 discusses the results, and Section 5 presents the conclusion and policy recommendations.

2 Literature review

Human capital is an important resource that helps to drive economic progress, societal development, and firm success. human capital drives growth and progress, with the Higher economic yield coming from skilled and informed workers. C.H. boosts invention and technology, which is crucial to long-term economic growth (Binh An et al., 2023; Friderichs et al., 2023; Z. et al., 2023). In addition, human capital is vital for social growth and can enhance poverty, health, cohesion, and crime rates. Education and training boost civil engagement, political involvement, and social progress (Ajide M. & Dada, 2022; Deming, 2022; Moyo et al., 2022). Human capital also affects a firm success. Employee training and growth boosts productivity, retention, and job happiness. human capital fosters creativity, which firms need to stay competitive and react to market changes(Capozza & Divella, 2019; Hu et al., 2023; Sisodia et al., 2021)

(Friedman et al., 2020) examined education inequality since 1970 and its relevance to well-being, human capital, and growth in predicting education-related 2030 SDG goals. By 2030, the world should have near-universal basic education, but higher and tertiary education remains problematic. Sub-Saharan Africa also has gender inequality. The best models work well across most geographies/ periods, so using numerous models for a single step is unnecessary. Supplementary information contains all forecast validity data. (Le Van et al., 2018) explored how social, human, and physical capital affected company performance simultaneously in Vietnam from 2005 to 2015 based on the hypothesis that social capital lowers the unit cost of physical capital. The theory's forecasts are supported by econometric data, and Spending on human social capital is influenced by firm performance. Over the past few years, wealthy countries like the United States of America (USA) and the United Kingdon (UK) have realized that spending on their people and merging knowledge and technology boosts and predict activity and economic output (Quintero-

quintero et al., 2021). Similarly, the results are relevant in the India and turkey cases (Abdul & Shaban, 2022; Ozyilmaz, 2020). The economic growth and human capital link have not yet been proven empirically, not only in established nations and the BRICS countries but also in emerging economies (Fatima et al., 2020; Khan et al., 2019; Musibau et al., 2019; Saqib et al., 2023; Sultana et al., 2022).

Moreover, numerous studies have studied the connection between human capital and economic development as a key element in deciding and increasing economic growth. According to research (Allui & Sahni, 2016), the interplay between C.H. and human resources supports the Kingdom of Saudi Arabia's economic expansion. The findings supported the significance and incorporation of human capital and development factors in promoting economic growth and urged lawmakers to prioritize raising human capital by implementing sensible educational policies. Within the direction of the Kingdom of Saudi Arabia towards a knowledge-based economy within Vision 2030, (Amirat & Zaidi, 2020) identified five knowledge economy components: employment, education, innovation, communication technology, and human capital, using annual data from 1991 to 2017.

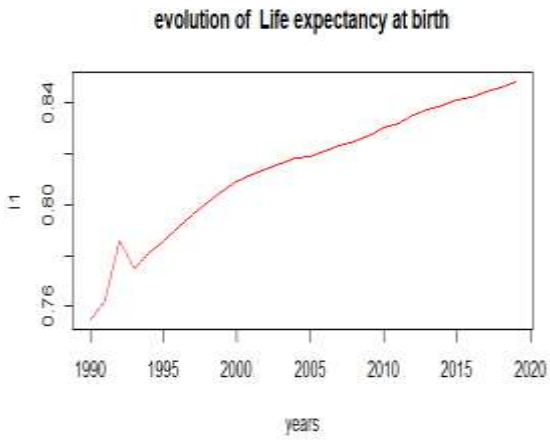
(Intisar et al., 2020) tested the effects of trade openness and human capital on economic development in 19 Asian nations from 1985 to 2017, found a significant and advantageous relationship between trade openness and human capital and economic performance in South Asia. Human capital and economic performance have a one-way causal link in both regions. (Sarwar et al., 2021) attempted to investigate the impact of financial development and human capital on economic performance from the perspective of the economies of 83 emerging countries during the period (2001-2002) used in this research and collected from the World Bank's global development indicators. The study concluded that financial development positively and significantly impacts economic performance. In emerging countries, human capital also positively impacts economic performance. Financial development and human capital interact positively and effectively with the economic growth of emerging economies.

Saudi Arabia must spend more in education and training in order to optimize synergies and minimize trade-offs between the sustainable development objectives, which will produce employment and capital. Education and training can help to achieve fiscal, social, economic, and health objectives while also protecting the ecosystem. (Singh et al., 2022). Human money enhances social and economic freedom through technology and fosters economic expansion.

3. Materials and Methods

This study uses artificial intelligence (AI) to measure the impact of human capital on economic performance in Saudi Arabia. It also aims to pinpoint the most significant economic drivers from 1990 to 2019. This research examines the link between human capital and economic performance in an oil-rent-dependent nation, in line with Saudi Arabia's Vision 2030 objectives.The independent variables in the study are mean years of education, expected years of enrollment, life expectancy at birth, and gross national income (GNI) per capita. The study employs the GDP as a proxy for economic performance. These data are collected from the World Bank. (2020).

The development of human resources is anticipated to be a key component of Saudi Vision 2030. The Saudi labor force is expected to grow to 8.6 million people by 2030, with a 44 percent participation rate, necessitating the creation of 203,000 new positions annually. The vision seeks to increase female involvement in the workforce from 22% to 30% while lowering the unemployment rate from 11.6 to 7.0% and reforming the educational system. Figure 1 plots the time series used in this estimation.



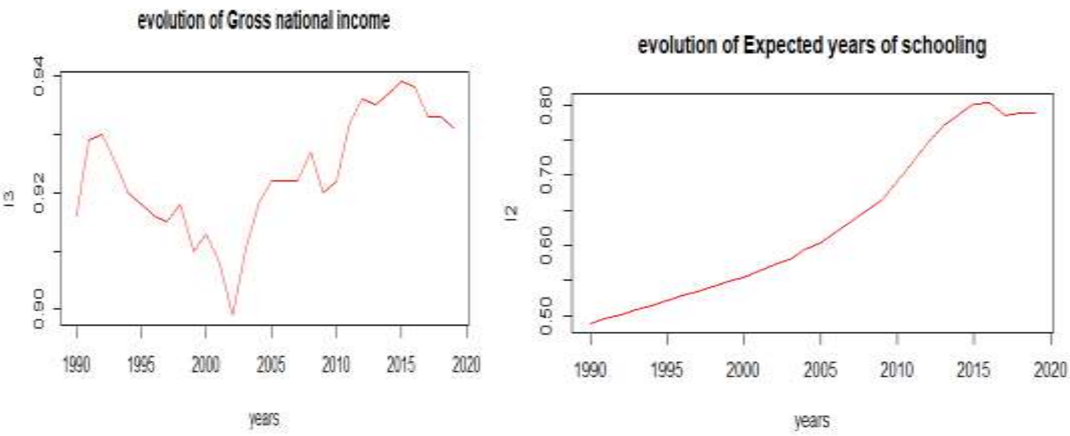


Fig.1: evolution of variables Durant 1990-2020

3.1. Model Definition

This study further examines the relationship between human capital and economic growth using the Artificial Neural Network (ANN) method to forecast how the GDP would respond to human capital development in Arabic Saudi Arabia in the context of Vision 2030. Also, this study employs traditional modeling, particularly vector autoregression (VAR) model.

3.1.1.Artificial Neural Network

Over the last six years, the addition of ANN instruments to the prediction and modeling of macro-economic data increased significantly. Data gathering, preparation, training, and testing with artificial intelligence feedforward and Y projection comprise the four steps of our research's procedure(Chen et al., 2023; Dieudonné et al., 2023; Magazzino et al., 2022). The neuron is the basic building component of any ANN process because it provides structural tuning to a particular mathematical function that receives inputs and produces an output. The fundamental ANN architecture is depicted in broad outlines in Figure 2. The current study employs an eventually linked ANN architecture with four hidden layers and one input layer with four inputs. Each layer's node is linked to a re-weighted node in the following layer. As a result, numerous attempts for each neuron within a particular hidden layer allow for a representation of input weights on neuronal outputs.

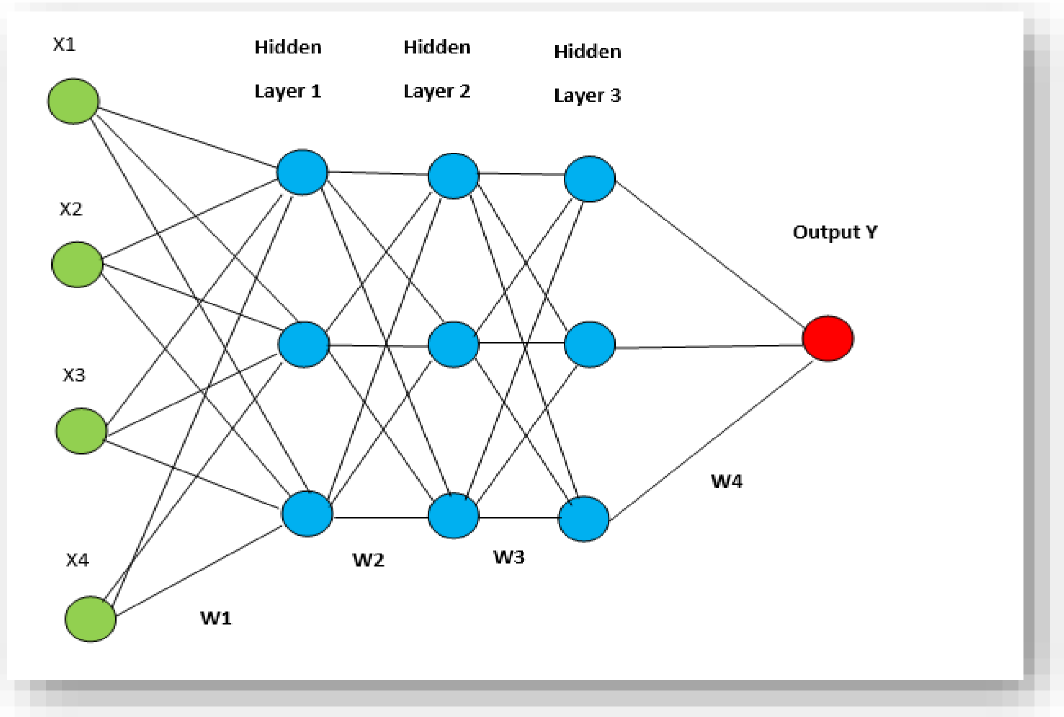


Fig.2: The Basic Artificial Neural Network (ANN)

3.1.2.**Vector Autoregression (VAR) Model**

Vector autoregression (VAR) technique is a statistical approach frequently used to predict networks of connected time series and examine the dynamic effects of random perturbations on the network of variables. By considering each endogenous component in the system as a product of the delayed values of each endogenous element

A VAR is represented mathematically as follows:

$$\mathbf{y_t} = \mathbf{M_1}\,\mathbf{y_{t-1}} + \ldots + \mathbf{M_n}\,\mathbf{y_{t-n}} + \mathbf{Zx_t} + \boldsymbol{\varepsilon} \ldots\ldots (\mathbf{1})$$

Where $\mathbf{y_t}$ is a $\mathbf{k}$-dimensional vector of dependent parameters, $\mathbf{x_t}$ is a $\mathbf{d}$-dimensional vector of independent variables, $\mathbf{M_1}$, $\mathbf{M_n}$, and $\mathbf{Z}$ are matrices of to-be-estimated values, and t is an array of innovations that may be simultaneously associated but have no relationship with their own time lags and unconnected via each of the other elements.

4.Results

After determining the variables and their data, we used two essential steps: (1) A pre-processing step for screening data and determining the most suitable determinants for this study. (2) A processing step was employed to model the problematic aspects of this study. In this step, we concentrate on co-integration processes and the VAR model to investigate the relationship between the study determinants in the short and long runs.

4.1.Descriptive Statistics

Preliminary numbers for a few different data sets are shown in Table 3. 30 observations were used to create this report. It is clear from Table 2 that all factors have positive mean values. The results are close to their corresponding means in terms of the median values, indicating that the likelihood of anomalies in the estimation process is very low, which will subsequently help the evaluation process. This research evaluated anomalies, normal distribution, and absent values for data filtering**.** The low standard deviation values indicate that the data elements remain relatively near their mean values.

Additionally, the skewness study reveals that the parameters are varied, with L1 and 13 having negative values and GDP and L2 being left-biased. Further, the results of the kurtosis analysis suggest that a few factors have more giant tails that are below the cutoff limit of three. Additionally, the J.B. test results show that the test averages are quite high, and in this situation, we must deny the null hypothesis of normalcy.

Tab.1: descriptive statistic

	GDP	L1	L2	L3
Mean	3.241800	0.813867	0.630033	0.923133
Median	2.665000	0.818500	0.599000	0.922000
Maximum	15.19300	0.848000	0.803000	0.939000
Minimum	-3.763000	0.755000	0.489000	0.899000
Std. Dev.	4.580413	0.025412	0.109979	0.010064
Skewness	1.079736	-0.654468	0.394166	-0.254140
Kurtosis	4.071668	2.552687	1.647091	2.442735
Jarque-Bera	7.264736	2.391752	3.064788	0.711116
Probability	0.026453	0.302439	0.216018	0.700782
Observations	30	30	30	30

4.2.Correlation finding

Figure 3 shows the correlation box between GDP and C.H. components. The finding reveals that GDP and the other factors have moderate, mostly negative correlations (between -0.32 and 0.09), as shown in the figure. However, there are significant positive correlations between L2 and L1, L3, which are equivalent to 0.91 and 0.70, respectively.

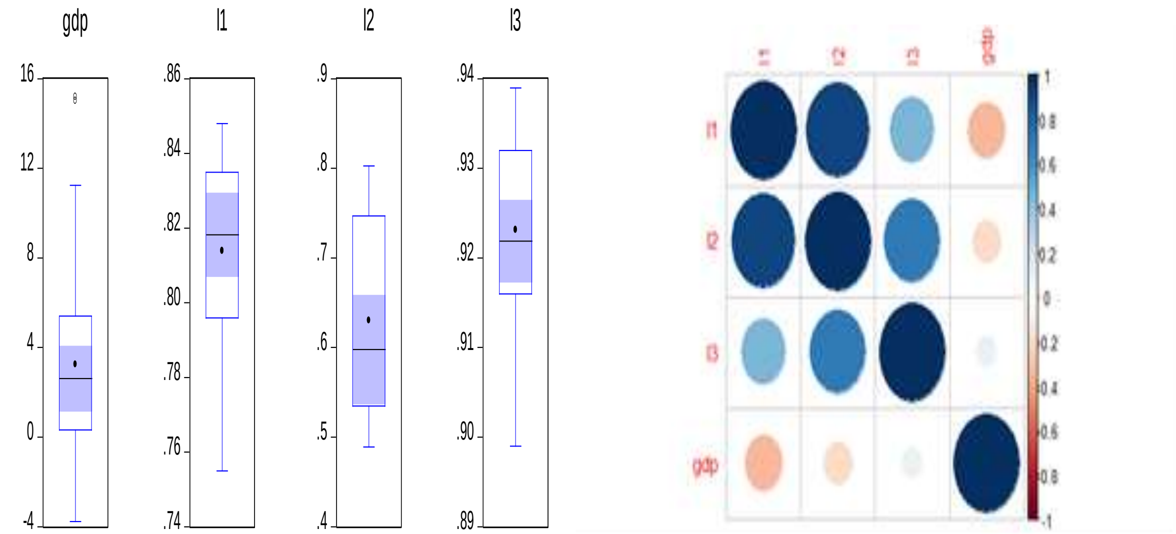


Fig. 3: correlation matrix and Box Plot

4.3. Stationary and optimal lag

The results of the unit root tests for these seizures are shown in Table 2 using (Dickey & Fuller, 1979; Phillips & Perron, 1988).
We obtained new results and graphics by applying the least squares method in the R programming language, but the estimate was insufficient. As a result, we turned to look for integration (the long-term equilibrium relationship between the dependent variable and its independent variables), and we discovered that all-time series were stationary at the first difference except for Variable L2, which was stationary until the second difference. There is no long-term connection when the second difference becomes stable, and autoregressive models To do this, VAR can determine the ideal level of delay, which must first be discovered.

Tab.2: results of stationarity by ADF and P.P. tests

		ADF test	P.P. test

		GDP	L1	L2	L3	GDP	L1	L2	L3
With Constant	t-Statistic	-4.8614	-3.9464	-0.0528	-1.5405	-4.6818	-1.0743	-0.7942	-1.4408
	Prob.	0.0005	0.0052	0.9457	0.4993	0.0008	0.7078	0.8053	0.5486
		***	***	n0	n0	***	no	no	no
With Constant & Trend	t-Statistic	-4.6406	-3.9055	-1.8114	-1.7855	-4.5462	-1.0754	-2.3088	-1.7855
	Prob.	0.0046	0.0248	0.6730	0.6856	0.0058	0.9149	0.4159	0.6856
		***	**	n0	n0	***	n0	n0	n0
Without Constant & Trend	t-Statistic	-3.9733	3.3509	3.6282	0.5029	-3.9201	2.4620	1.1936	0.4922
	Prob.	0.0003	0.9995	0.9998	0.8181	0.0003	0.9951	0.9362	0.8155
		***	n0	n0	n0	***	n0	n0	n0
		d(GDP)	d(L1)	d(L2)	d(L3)	d(GDP)	d(L1)	d(L2)	d(L3)
With Constant	t-Statistic	-8.1141	-7.3972	-2.0620	-5.2572	-5.2027	-3.2934	-2.0560	-5.2612
	Prob.	0.0000	0.0000	0.2605	0.0002	0.0002	0.0267	0.2628	0.0002
		***	***	n0	***	***	**	n0	***
With Constant & Trend	t-Statistic	-8.1605	-9.2639	-1.9009	-5.2641	-5.0879	-2.7208	-1.9185	-5.2641
	Prob.	0.0000	0.0000	0.6274	0.0011	0.0018	0.2376	0.6183	0.0011
		***	***	n0	***	***	n0	n0	***
Without Constant & Trend	t-Statistic	-8.1276	-5.0600	-1.3348	-5.3858	-5.2833	-5.7466	-1.4301	-5.3911
	Prob.	0.0000	0.0000	0.1642	0.0000	0.0000	0.0000	0.1391	0.0000
		***	***	n0	***	***	***	n0	***

We are given six factors to choose the optimal lag degree using the R and Eviews 9.0 software. By assembling the factors with the lowest values, as shown in the chart, we identified them. The first-degree lag appears optimal according to S.C., H.Q., FPE, and L.R., based on the results of the different criteria (S.C., H.Q., FPE, L.R., and AIC) used to establish the ideal lag length in the model. The AIC criterion, however, indicates that a fourth-degree lag might be ideal. The best lag length is eventually determined using the robustness of the AIC criterion.

Tab.3: Results of the lag test

Lag	LogL	LR	FPE	AIC	SC	HQ
0	236.6418	NA	4.47e-14	-19.38682	-19.19048	-19.33473
1	272.9703	57.52003*	8.42e-15*	-21.08085	-20.09914*	-20.82041*
2	287.4270	18.07090	1.09e-14	-20.95225	-19.18517	-20.48344
3	303.5122	14.74479	1.56e-14	-20.95935	-18.40690	-20.28218
4	328.3830	14.50798	1.80e-14	-21.69858*	-18.36076	-20.81306

* Indicates lag order selected by the criterion
L.R.: sequential modified L.R. test statistic (each test at 5% level); FPE: Final prediction error;
AIC: Akaike information criterion; SC: Schwarz information criterion
H.Q.: Hannan-Quinn information criterion

4.4. - Estimation model VAR:

In this step, we estimate the VAR model at the 4th lag. Then we obtain four equations with a lot of information about the significance of the model and its explicative power. Still, we choose the first equation only, which shows the difference in GDP here as a dependent variable:

Tab.4: VAR model estimation

	D(GDP)	D(L1)	D(L2,2)	D(L3)
D(GDP(-1))	-1.631410	-0.000186	-0.002312	-0.000510
	(0.78452)	(0.00013)	(0.00200)	(0.00108)
	[-2.07949]	[-1.39820]	[-1.15296]	[-0.47094]
D(GDP(-2))	-1.579215	-9.25E-05	-0.000645	-0.000199
	(0.81101)	(0.00014)	(0.00207)	(0.00112)
	[-1.94721]	[-0.67248]	[-0.31097]	[-0.17802]

D(GDP(-3))	-0.263279	-6.06E-05	0.000198	0.000486
	(0.58016)	(9.8E-05)	(0.00148)	(0.00080)
	[-0.45380]	[-0.61639]	[0.13342]	[0.60759]
D(GDP(-4))	0.100153	3.70E-06	0.000269	0.000388
	(0.32426)	(5.5E-05)	(0.00083)	(0.00045)
	[0.30887]	[0.06732]	[0.32447]	[0.86682]
D(L1(-1))	-2758.773	0.512496	3.919440	1.728778
	(2495.85)	(0.42325)	(6.37857)	(3.44317)
	[-1.10535]	[1.21086]	[0.61447]	[0.50209]
D(L1(-2))	419.5746	0.358480	-5.890019	-4.654336
	(2380.99)	(0.40377)	(6.08503)	(3.28472)
	[0.17622]	[0.88783]	[-0.96795]	[-1.41697]
D(L1(-3))	-83.60424	-0.120304	-0.477424	-0.495649
	(589.409)	(0.09995)	(1.50634)	(0.81313)
	[-0.14184]	[-1.20361]	[-0.31694]	[-0.60956]
D(L1(-4))	8.876400	-0.083815	-0.113105	-0.059657
	(297.050)	(0.05037)	(0.75916)	(0.40980)
	[0.02988]	[-1.66385]	[-0.14899]	[-0.14558]
D(L2(-1),2)	-101.5578	-0.015078	-0.287715	0.010635
	(133.663)	(0.02267)	(0.34160)	(0.18440)
	[-0.75981]	[-0.66519]	[-0.84226]	[0.05768]
D(L2(-2),2)	-209.9934	-0.015391	-0.516498	0.330373
	(374.014)	(0.06343)	(0.95586)	(0.51598)
	[-0.56146]	[-0.24266]	[-0.54035]	[0.64029]
D(L2(-3),2)	443.5903	0.036505	1.091844	0.050415
	(429.418)	(0.07282)	(1.09745)	(0.59241)
	[1.03300]	[0.50130]	[0.99489]	[0.08510]
D(L2(-4),2)	1077.473	-0.004243	0.918728	0.927265
	(483.632)	(0.08201)	(1.23601)	(0.66720)
	[2.22788]	[-0.05174]	[0.74330]	[1.38978]
D(L3(-1))	225.6496	0.097149	0.934750	-0.020964
	(576.355)	(0.09774)	(1.47298)	(0.79512)
	[0.39151]	[0.99397]	[0.63460]	[-0.02637]

D(L3(-2))	-561.2539	-0.091451	-1.933741	-0.853627
	(476.359)	(0.08078)	(1.21742)	(0.65717)
	[-1.17822]	[-1.13208]	[-1.58839]	[-1.29895]
D(L3(-3))	-1071.052	0.017927	-0.716402	-0.689348
	(527.185)	(0.08940)	(1.34731)	(0.72728)
	[-2.03164]	[0.20052]	[-0.53173]	[-0.94784]
D(L3(-4))	-478.3857	-0.066121	-0.756066	-0.402515
	(368.433)	(0.06248)	(0.94160)	(0.50828)
	[-1.29843]	[-1.05828]	[-0.80296]	[-0.79192]
C	6.725515	0.000727	0.007910	0.011565
	(3.43589)	(0.00058)	(0.00878)	(0.00474)
	[1.95743]	[1.24758]	[0.90085]	[2.43987]
R-squared	0.813625	0.894700	0.489376	0.642171
Adj. R-squared	0.387626	0.654014	-0.677763	-0.175723
Sum sq. resids	116.5615	3.35E-06	0.000761	0.000222
S.E. equation	4.080642	0.000692	0.010429	0.005630
F-statistic	1.909921	3.717298	0.419295	0.785152
Log likelihood	-53.01891	155.3534	90.24762	105.0448
Akaike AIC	5.834909	-11.52945	-6.103969	-7.337069
Schwarz SC	6.669364	-10.69499	-5.269514	-6.502614
Mean dependent	0.004958	0.002583	-0.000292	0.000542
S.D. dependent	5.214589	0.001176	0.008051	0.005192

Determinant resid covariance (dof adj.)	2.12E-15
Determinant resid covariance	1.53E-17
Log likelihood	328.3830
Akaike information criterion	-21.69858
Schwarz criterion	-18.36076
Number of coefficients	68

When we r-estimate only this equation, we find that many endogenous variables do not significate, but when we filter here a condition value R- adjusted rise, the table 4 shows the final results.

The results indicate that all explanatory variables may impact the KSA economic growth as measured by the autoregressive VAR model for gross domestic product. With the first variable, the average number of years spent in school, the gross domestic product will fall by 2142.9% whenever the latter changes by one unit. This inverse relationship can be explained by the fact that education outputs in the kingdom hinder economic growth. As is well known, education in the kingdom still relies on indoctrination pedagogy. It lacks the competencies and innovative pedagogy that would enable the student to exit from school with the ability to be creative and inventive. The educational achievements of the monarchy and its GCC neighbors, like Qatar and the UAE, are comparable. The results align with the previous research (Amirat & Zaidi, 2020).

The expectation of life years in the previous third and fourth times appears to have a positive relationship with the second variable in this case, as whenever they increase by one unit, respectively, the crude internal product variable will change by 340.9 units for the first and by 765.9 units for the second. This positive correlation can be explained by an increase in the average life expectancy from year to year, made possible by the ease of living and privileges and the rapid healthcare advancement. After economic sectors were once solely dependent on oil rents, this increase helped to some degree with their growth and diversification This finding corroborate with the previous study (Intisar et al., 2020).

Regardless of the third variable in its second and third prior times, these effects are distinct, indicating that the student's test was only partially met. Whenever the crude internal product increases by one unit, the third variable in the two prior times decrease by 792.54 and 229.26, respectively. In its last fourth time, the third variable does not affect it alone. Still, the Fisher test indicates its existence is required in combination with the other variables and the constant calculated at 6.30.

Furthermore, the explanatory variables explained 77.39% of the change in the dependent variable, which is a reasonable number that allows it to define less than 25% of the variance only with the help of other variables. This ratio shows how crucial the three elements of the C.H. indicator are for affecting economic development. The residuals are normally distributed, there is no issue with autocorrelation between errors, and there is no variance difference between errors given the computed D.W. value, which is very near to 2. Because the least squares technique was used to pass all of these tests, our model is legitimate for estimation and prediction and can be used to understand policies.

The lack of errors autocorrelation is indicated by the Durbin-Watson (D.W.) statistic value of 2.27. The Residual Portmanteau Test findings in Appendix 3 support this conclusion. The Skewness, Kurtosis, and Jarque-Bera tests and the residual distribution tests show that the residuals are normally

Tab.5: Estimators of the required equation

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-1.314451	0.200763	-6.547282	0.0000
C(2)	-0.968794	0.333013	-2.909180	0.0108
C(5)	-2142.996	718.4010	-2.983008	0.0093
C(11)	340.9319	184.3917	1.848954	0.0843
C(12)	765.9577	247.8064	3.090951	0.0075
C(14)	-622.2005	247.8592	-2.510298	0.0240
C(15)	-792.5466	278.0778	-2.850090	0.0122
C(16)	-229.2631	138.9134	-1.650403	0.1196
C(17)	6.301813	2.130258	2.958240	0.0098
Determinant residual covariance		5.890532		

Equation: D(GDP) = C(1)*D(GDP(-1)) + C(2)*D(GDP(-2)) + C(5)*D(L1(-1))+ C(11)*D(L2(-3),2) + C(12)*D(L2(-4),2) + C(14)*D(L3(-2)) + C(15)*D(L3(-3)) + C(16)*D(L3(-4))+ C(17)

Observations: 24

R-squared	0.773953	Mean dependent var	0.004958
Adjusted R-squared	0.653395	S.D. dependent var	5.214589
S.E. of regression	3.069992	Sum squared resid	141.3728
Durbin-Watson stat	2.276096		

4.5. **ANN experiments**

As shown in Figure 4, we determine the outcome to forecast this part's GDP and C.H. components.

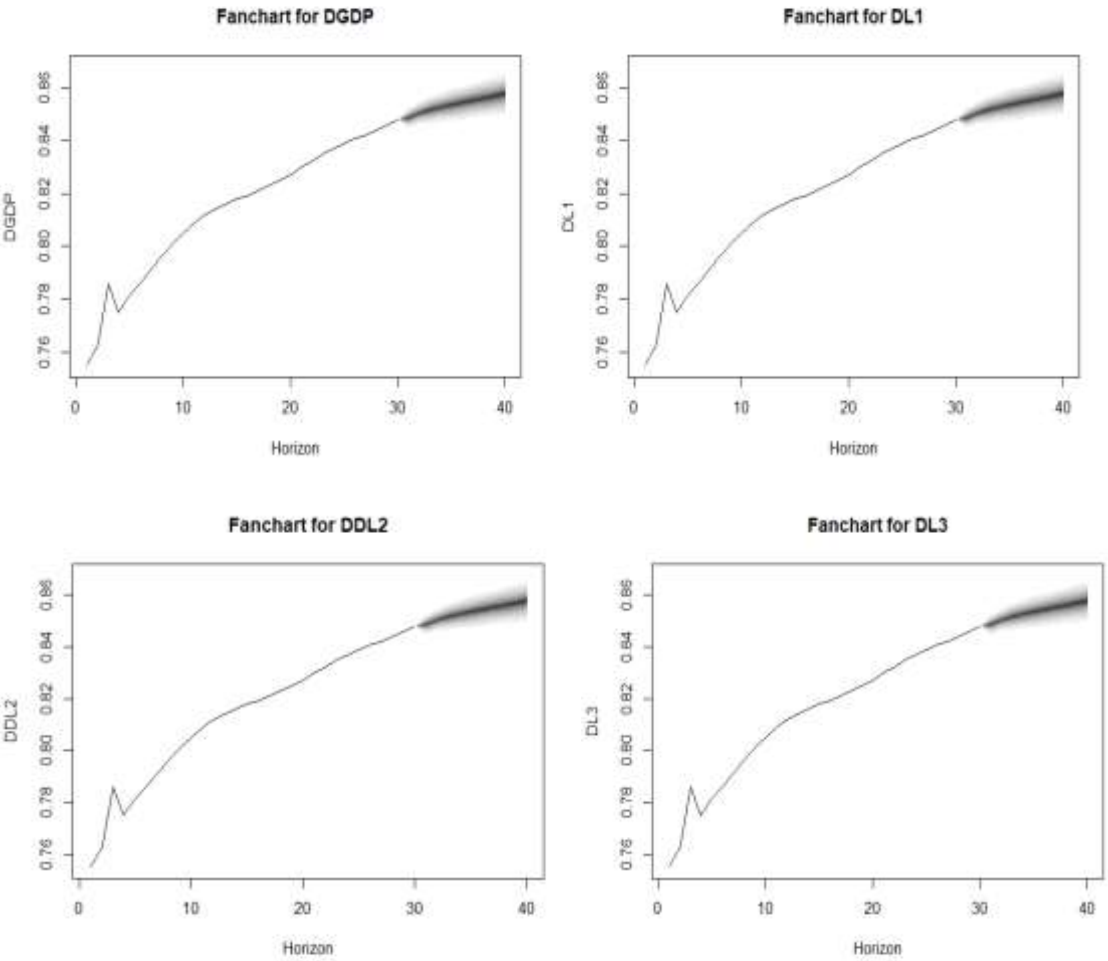


Fig.4: Results of prediction by ANN in R

The Feature findings using ANN are shown in Table 5. The predictive system achieves good feature outcomes through the assessments of the statistics test. The results demonstrate that when all factors are considered, the MAE, MSE, RMSE, and MAEP have a performance rating for a feature. The ANN algorithm's findings demonstrate the same effects of deep learning and highlight how crucial it is to combine L1, L2, and L3 to forecast economic development.

Tab.6: Feature results using ANN

MAE	**MSE**	**RMSE**	**MAPE**	**R^2**
0.79	1.58	0.99	0.60	0.78

5 Conclusion and Policy Recommendations

This research explores how the GDP in Saudi Arabia would react to the development of C.H. in the framework of Vision 2030. This study further considers the connection between C.H. and economic growth. It does this by using Artificial Neural Network (ANN) techniques. The results show that GDP is crucial in creating a trustworthy analysis of projected increases in C.H. These findings have significant ramifications, including contrasting artificial neural network (ANN) studies' superior forecast accuracy to traditional models. With a population of over 30 million and over 9.7 million labor force, Saudi Arabia is experiencing fast population growth. Saudi Arabia's population is expanding by 2.7% annually due to immigration and a high birth rate.

The labor force is also growing due to immigration and better involvement rates among Saudi men and women. Saudi Arabia has a robust educational structure, tiny class sizes with an average of 11 pupils, and high government spending on education, all of which contribute to the country's high level of C.H. More than 80 vocational colleges, 25 public universities, eight private universities, and 20 private colleges comprise Saudi Arabia's vast network of schools for higher education and continuing education. . The finding of this study has many implications. Policymakers can promote lifetime learning by offering opportunities for lifelong learning and skill development: adult schooling, vocational training, and online learning classes. Innovation and entrepreneurship drive economic growth, and policymakers can support them by funding startups and small businesses and creating an environment that encourages them. Healthcare access boosts human wealth and economic growth. By fostering healthy habits and preventative healthcare, policymakers can boost economic growth, especially for low-income families. Policymakers also should limit Income inequality chances for people to build their C.H. and engage in the market, limiting economic growth. Progressive taxes, affordable housing, healthcare, and education can reduce wealth disparity.

Funding:

The authors gratefully acknowledge financial support from The Deanship of Scientific Research, King Faisal University (KFU) in Saudi Arabia. The present work was done under Project Number (GRANT 287).

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