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THE NEXUS BETWEEN ARTIFICIAL INTELLIGENCE AND ECONOMIC DEVELOPMENT: EVIDENCE FROM EGYPT

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ABSTRACT

This study attempts to explore the causality-in-meaning between artificial intelligence (AI) and economic development in the context of the Egyptian economy. The research assumes a mutual causality: AI shapes economic growth, measured by the real GDP, while at the same time economic growth promotes AI development. In order to study the intricate dynamics underlying this relationship, we used a traditional econometric model applying the Johansen cointegration test and the Vector Error Correction Model (VECM). The results of this study present evidence of a bidirectional causality between AI and real GDP growth in the short run. In particular, real GDP growth is found to spur AI growth, and AI growth is found to support the growth of real GDP. In the long run, the paper shows a unidirectional causal relationship between real GDP and hours worked, with real GDP growth being found to cause increasing labour supply. As well, in the long-run, a unidirectional relationship is found to exist from real GDP to real capital accumulation, and real investment expenditures are found to be a determinant of real GDP growth. These findings indicate that AI, economic growth and macroeconomic determinants are interrelated and endogenous in Egypt, emphasizing the need to consider the effects over longer periods of time when examining these intricate relationships.

KEYWORDS: Economic Growth, Egypt, Real Gross Domestic Product, Artificial Intelligence.

1. INTRODUCTION

AI has very quickly emerged as a disruptive force in today's world economy having the potential to redefine industries, sectors, and in fact economies themselves. In recent decades, AI has evolved from a niche area of research to a key technology in finance, industry, medicine, and governance (Brynjolfsson et al., 2019, 1; Damioli et al., 2021; Elkomy et al., 2021). The combination of advanced machine learning algorithms stronger computational capacities, and the access to a large scale amount of data has enormously increased AI, reaching an impact in economic developments that was not conceivable in the past (Brem et al., 2023). Among the ways AI helps is its ability to aid in the early detection and diagnosis of disease; in the identification, monitoring, and control of potential epidemics; in the application of advanced radiology and pathologic imaging. At the same time, AI is used across financial services for fraud prevention and anti-money laundering. Also, innovations in AI, like robo-advisory services, help in offering personalized investment solutions to meet financial goals and make the best of clients' money. Also, AI can support autonomous transportation and delivery systems, improves and optimaze traffic control and enhances security as part of transportation systems (Elkomy et al., 2021).

AI also drives economic growth by fueling expansion on both the supply and demand fronts. AI also increases the productivity when bu siness get digitized in their activities through robotics and driveless cars AI improves and fuels the current workforce by arming it with AI technologies, and create new products and new services (Brem et al., 2023). The demand pull from consumers for personalized and/or enhanced goods and services can also be facilitated through AI. AI is expected to add $15.7 trillion to the world economy by 2030 (Gonzales, 2023). This paper attempts to explore the linkage between artificial intelligence and economic growth in Egypt over the period 1980-2023. The research is built on the theory that artificial intelligence fuels economic growth and that economic growth stimulates artificial intelligence. The study seeks to validate this hypothesis through an inductive approach to studying the nexus between AI and economic development in Egypt. In addition, the research applies inductive approach through the data and statistics gathering to make the target of the research.

To test the validity of the hypothesis, the analysis suggests splitting research into seven parts and an introduction. (MI) Part 2 will summarize the literature. Its third part will cover the promises and perils of artificial intelligence. It will also detail the attributes of the world market for developed AI companies. It will also feature coverage of Egypt's work in the field of artificial intelligence. Methodology of the study will be described in Part 4. Then part 5 goes to the findings from the study. The final part 6 will discuss the Conclusion of the research.

2. LITERATURE REVIEW

2.1. Previous Studies

Many earlier studies have been conducted on artificial intelligence and economic growth. These comprise research in (Fan & Liu, 2021), (Gonzales, 2023), Trabelsi (2024), Kalai et al. (2024), Tang et al. (2024), Fan and Liu (2021) found that the use of AI played a significant effect on economic growth. Based on the data of 28 provinces in China in 2005-2018, this article draws a conclusion that the development of artificial intelligence not only directly affects economic growth, it also has an intermediate influence on the economic fluctuation through the impact on the industrial structure, leading to the economic downturn. The results indicate that such a mediating effect plays an important role in eastern, central and western parts of China. Regression analysis also showed that the advancement of AI technology did not lead to economic growth before the 2008 crash. Research and development and the use of AI, though, helped the Chinese economy recover during upswing. Subsequently, AI has played an increasingly important role in driving high-quality and sustainable economic growth in China. Gonzales (2023) tried to measure how much ai would affect the economy, and focused in particular on long-run economic growth. The research hypothesized a positive relationship between AI and economic growth. We tested this hypothesis using a cross-country dataset which spanned over multiple countries from 1970 to 2019. We use the number of patent applications filed on AI as the indicator of AI. The results of the study revealed the positive relationship with economic growth exerted by artificial intelligence going beyond that of the volume of sum of patent applications on economic growth. In addition, the results implied that the impact of AI on growth was both stronger in developed countries and stronger in the later part within our sample period.

A review by Trabelsi (2024) of an emerging literature on the projections of what future developments in AI would have on the economy. This review searched the most recent publications, including papers and reports, particularly from academics, consultancies and think tanks. It was determined that AI is a catalyst for productivity and growth. It can also significantly improve efficiency and assist in decision-making based on large datasets. But the report also highlighted major risks associated with such change - labour market polarisation, rising inequality, structural unemployment and the growth of new unattractive industrial structures. Kalai et al. (2024) tried to quantify the effect of AI on growth for 30 European countries over the 2000-21 period. This study made use of symmetric (PMG-ARDL) and asymmetric (PMG-NARDL) modelling. The findings of the ARDL model revealed that AI has a positive effect on economic growth. In the NARDL model, the LR dynamic womens and AIs were positively impact with ER 0.217% as affected of the Growth. The economic growth is noted to have risen by 0.026% as a result of positive shocks on positive AI variable. In contrast, negative shocks had negative effects, reducing economic growth by 0.029 per cent.

Tang et al. (2024) attempted to offer a systematic review of current studies on the implications of artificial intelligence for economic development. The report concluded that artificial intelligence was a major contributor to increased productivity, innovation and economic growth. The main application fields were summarized as intelligent decisions, transformation of labor market, the industry and social governance. But the study also highlighted that artificial intelligence raises issues that include ethics, potential loss of jobs, and potential privacy threats - all of which call for policy measures to ensure that positive economic impacts can be maximized, while negative ones can be avoided.

2.2. Synthesis of Previous Studies

The above discussion of prior work suggests that, in spite of substantial research efforts for artificial intelligence and economic development (Benvenuti et al., 2023), there is no clear consensus. Therefore, the objective of the current research is to analyze the link between artificial intelligence and economic growth in the example of Egypt. The current paper is different from previous studies in that it contributes to the empirically applied analysis of the Egyptian economy, using the fairly most up to date data across the 1980-2023 period. It aims to also test the causation by using an error correction model, a technique ranked among modern econometric approaches.

3. OPPORTUNITIES AND CHALLENGES OF ARTIFICIAL INTELLIGENCE

The embedding of artificial intelligence (AI) into the economic system offers large opportunities, and is accompanied by large discontents (Brynjolfsson et al., 2018). AI-powered intelligent systems have shown great promise in productivity improvement, innovation stimulation, and decision-making process improvement, and are expected to drive economic growth as a result (Bogachov et al., 2020). Moreover, AI technologies have enabled the transition to the forth industrial revolution and cooperative smart factories and supply chains, promoting production efficiency. Furthermore, AI in financial markets and governance enhanced resource allocation and service delivery (Damioli et al., 2021).

On the other hand, AI raises fears about job loss, rising inequality, privacy (Athey et al., 2020), and ethics (Elkomy et al., 2021). Discussions continue about whether AI's economic benefits are worth its social and ethical costs. However, the literature on the role of AI for economic development appears to be rather fragmented, despite the increasing relevance of AI in economic sphere.

3.1. Characteristics of the Global Market for Emerging AI Companies

The features of the global market of nascent artificial intelligence firms are illustrated by means of how much artificial intelligence companies are and how many investments are made on a worldwide scale done in artificial intelligence (Brynjolfsson et al., 2019), and how the global artificial intelligence market size index (Damioli et al., 2021). As for the number of artificial intelligence companies and that of private-invested value across the world, they are illustrated in Table (1).

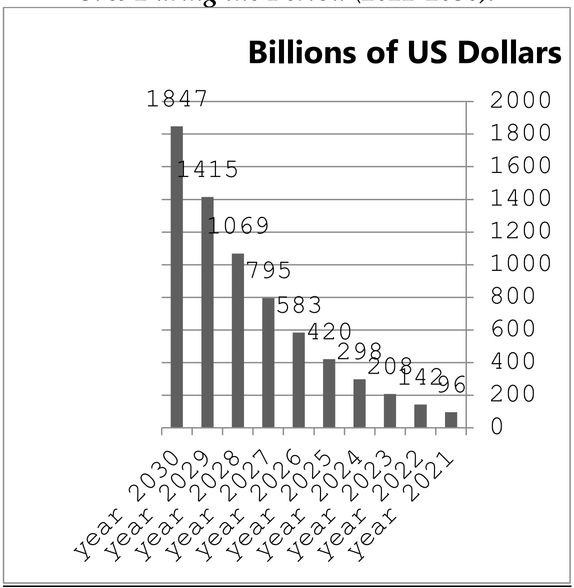
Table 1: Number of Artificial Intelligence Companies and Global Private Investment.

No.	Country	Num. of Emerging AI Companies (2013-2022)	Private Investment (2013-2022) in Billions of US Dollars
1	USA	4643	249
2	China	1337	95
3	UK	630	18
4	Israel	402	11
5	Canada	341	9
6	France	338	7
7	India	296	8
8	Japan	294	4
9	Germany	245	7
10	Singapore	165	5

Source: Information and Decision Support Center, Egyptian Cabinet (2023).

Table (1) shows that as a market for the artificial intelligence companies United States of America is dominant with an approximately 4643 nascent specialized firms with nearly the amount of 245 billion US dollars of investment 1. About 1,337 Top Startups in categories such as Cyber Security, Big Data, Blockchain, and Quantum Computing along with others, China comes in at second place in corporate and start-up AI company creation with almost 1,337 companies and an investment volume estimated at nearly 95 billion US DOLLARS. The artificial intelligence market size index worldwide in 2021-2030 could be shown as Figure (1).

Figure (1): Global Artificial Intelligence Market Size During the Period (2021-2030).



Source: Information and Decision Support Centre, Egyptian Cabinet (2023).

Figure (1): The rapid rise of the Global AI Market from (2021-2030). The market was valued at about 96 billion U.S. dollars in 2021, and looks like it will grow to around 208 billion U.S. dollars by 2024. It is estimated to be almost 1.8 trillion US$ by 2030. This growth isdue in part to greater dependence on information technology, significant strides in scientific R&D, as well as governments' rising interest in artificial intelligence.

3.2. Egypt's Efforts in the Field of Artificial Intelligence

It is clear that Egypt is visibly concerned with improving the penetration of AI applications through the following projects (Elkomy et al., 2021)

Egypt's Vision 2030: A national strategy aimed at building a digital society based on 3 key vectors; digital transformation, digital skills and competence, digital creativity and innovation.

Launching of AI Platform: An exclusive platform on artificial intelligence has been launched for aggregating all initiatives in capacity building in AI and showcasing growing AIinnovationn in India.

Knowledge Sharing: To support the exchange of best practices between the government, industry, academia or other related contacts regarding artificial intelligence applications, interchange, principles and ethics.

Establishment of Technology and Excellence 44Innovation Centers and Smart Cities: The creation of innovation centers is a pillar of the Digital Egypt Initiative, and the City of Culture and Arts situated in the New Administrative Capital is designed with the latest global technologies. This is conducive to establishing a knowledge-based society and an attractive atmosphere for the inflow of global investments, resulting in a higher degree of economic growth and development.

Focus on Smart City Development: Egypt is giving importance to the creation of several new smart cities that are powered with artificial intelligence.

Enabling the private sector in digital transformation/ AI The Egyptian government is heavily promoting the adoption of digital transformation systems, AI applications and innovation in the various works in the private sector, including in banking, real estate and commerce. This is being undertaken in partnership with telecoms and infotech companies and aims to 1) develop local human capital, 2) increase production, 3) reduce costs and 4) raise returns.

4. METHODOLOGY

The study model To examine the impact of artificial intelligence as a causal to real economic growth in the Egyptian economy, the study has specified the variables and specified the path of the model based on previous studies using the Cobb-Douglas model (Juodis et al., 2021) to establish the impact of the impact of real foreign debts on real economic growth in Egypt. Mathematically, the Cobb-Douglas production function is given by:

$$y_t = A\ K_t^{\alpha} L^{\beta} \qquad (1)$$

where: Y is economic development in Egyptian economy RGDP is the real GDP. A is a measure of technology (understood to remain constant). K represents real capital accumulation. L represents the labour force. α is the real capital accumulation's ouptut elasticity. β is the output elasticity with respect to labour.

Since the study aims to explore the relationship between artificial intelligence (AI) and economic growth in Egypt, the variable representing residents' patent applications (denoted as R) is introduced as an explanatory factor. Patent applications are used here as an indicator of the country's capacity to generate new knowledge and innovations, which is a key aspect of AI development.

By including R in the production function (equation 1), the model explicitly accounts for the contribution of AI-related knowledge production to economic output. The modified equation (2):

$$y\_t = A + K\_t^\alpha + L^\beta + R\_t^y \quad (2)$$

shows that output (yt) depends not only on traditional inputs—capital (Kt) and labor (L)—but also on the level of AI knowledge production (R_t), each raised to their respective elasticities (α, β, and y). This allows the study to quantify how advances in AI, as measured by patent activity, influence economic growth in Egypt.

If we then take the logarithm of both sides of Equation (2) we obtain a linear equation:

$$\log y\_t = b\_0 + b\_1 \log K\_t + b\_2 \log L\_t + b\_3 \log 〖R〗\_t + \epsilon\_t \ldots (3)$$

The relation between each explanatory variable and economic development is tested bi-variately (in both the short and long-runs) based on Equation (3). Note that given that the variables are expressed in their logarithmic form, the partial derivatives correspond to the elasticity of the growth rate of the real economic development with respect to the explanatory variables. In particular, b1 denotes the elasticity of real GDP with respect to real capital formation, b2 denotes the elasticity of real GDP growth with respect to labor and b3 denotes the elasticity of real GDP with respect to artificial intelligence. Here, ϵt denotes a hypothetical error term that will be supposed to satisfy standard statistical properties, such as a zero mean and constant variance.

As for the data used in the experiments about the state of the Egyptian economy from (1980–2023), it was obtained from international sources, in particular the World Bank. Moreover, to calculate the real values of these variables, i.e., the real GDP and the real capital accumulation, we have used the Consumer Price Index (CPI – Base year 2010 = 100). Local sources (including the Ministry of Planning and Economic Development) complemented these data.

4.1. Results

According to the method of our research, there are three types of tests used, including unit root tests, cointegration tests and error correction model.

5.1. Unit Root Test for Stationarity of Time Series

The Unit Root Test diagnoses the nature of the time series of the labour force (L) as a real variable, economic development as measured by real gdp (Y), capital accumulation (K), and artificial intelligence (R) of the period (1980-2023). This is to establish the stationarity of each series and the order of integration for each variable separately. Notwithstanding the numerous unit root tests to choose from, this paper will make use of two test; ADF test and PP test. 2) shows the results of the ADF unit root test for all the variables in the study.

Table 2: ADF Unit Root Test Results for Levels and First Differences of Variables.

ADF-test & PP_test								
Time Series	level				First difference			
	One direction		General direction		One direction		General direction	
	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*
log(Y)	2.07	1.00	-2.38	0.39	-7.27	0.00	-8.32	0.00
log(L)	-1.10	0.71	-2.14	0.51	-5.44	0.00	-5.34	0.00
log(K)	-0.65	0.85	-1.30	0.88	-5.32	0.00	-5.28	0.00
log(R)	-1.97	0.30	-1.40	0.85	-5.63	0.00	-6.18	0.00

Source: Prepared by the researcher based on the outputs of the EViews program.

Table (2) reports the Dickey-Fuller test results (Born & Breitung, 2016), which show all-time series of the growth rate of real economic development, the growth rate of the labor force, the growth rate of real capital accumulation and AI are not stationary at their original level with or without a trend. That is, this provides evidence in favor of the acceptance of the null hypothesis of unit root, indicating that these time series are not stationary at 5% level of significance. The point to notice is that all the time series are stationary after being differenced once, with or without a trend at the 1% critical value or less. For the Phillips-Perron test of unit root, Table (3) shows the PP test on the unit root of the study variables.

Table 3: PP Unit Root Test Results for Levels and First Differences of Variables.

ADF-test & PP_test								
Time Series	level				First difference			
	One direction		General direction		One direction		General direction	
	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*
log(Y)	2.69	1.00	-2.56	0.30	-7.28	0.00	-8.83	0.00

log(L)	-1.10	0.71	-2.25	0.45	-5.36	0.00	-5.25	0.00
log(K)	-0.63	0.85	-1.52	0.81	-5.32	0.00	-5.28	0.00
log(R)	-2.30	0.18	-1.04	0.93	-5.63	0.00	-6.42	0.00

Source: Prepared by the researcher based on the outputs of the EViews program.

The results in Table (3) corroborate the conclusion of the Phillips-Perron test, consistent with the Dickey-Fuller test, that the individual time series for the growth rate of real GDP, the growth rate of the labour force, the growth rate of real capital accumulation and AI at the level are non stationary at all of the levels of these three variables (excluding when the time series levels of these three income generating variables are augmented with trend in the denominator of the top of these three individual column of panel A). This implies that the null hypothesis of a unit root is not rejected and that the time series cannot be stationary in levels with or without an intercept and trend term. In addition, estimates of the Phillips-Perron test are in line with those of the Dickey-Fuller first difference test (with the intercept and intercept plus trend) at 1% significant level.

4.2. Johansen-Juselius Cointegration Test Results

The Engle–Granger test is a useful test for investigating the presence of cointegration among variables. Unfortunately, it does not give any idea about the order of cointegration. So on this problem the Johansen test comes to the rescue, as it's able to determine the amount of these vectors, contrary to other cointegration tests. In general, the Johansen test is used in addition to the Engle-Granger test. After a single cointegrating relationship is found using the Johansen-Juselius Cointegration test, the presence of a single cointegrating relationship among variables is further tested using Johansen-Juselius test and error correction model equations estimated (Paltasingh & Goyari, 2013). Results The results of the Johansen-Juselius test are reported in table (4).

Table (4) results indicate that the calculated value of the trace test under under both the null hypothesis (H1.1) and (H1.2) pass the critical values at 5 per cent significance level that uses either intercept or intercept and trend constraint. This observation implies that the null hypothesis (H0) of no cointegration is rejected and the alternative hypothesis (H1) is endorsed, which implies cointegration among the growth rate of real GDP and its determinants, namely artificial intelligence, labor force, and real capital accumulation.

Moreover, as indicated in Table (4), the second hypothesis is not statistically significant under intercept and trend assumed in trace test at the level of 1% or 5%. Moreover, the computed trace test statistic is not greater than the critical values, causing the null hypothesis that the number of cointegrating vectors does not exceed one not to be rejected. This suggests that there is no second cointegrating vector among the study variables as per both the Trace test and maximum eigenvalue test at 5% or 1% level of significance. The test based on trace and maximum eigenvalue have a conflict at 5% significance level. Nevertheless, when the two tests disagree, trace test results are generally held to be more trustworthy, a conclusion supported by work such as that of Lütkepohl et al. (2001).

Table 4: Johansen-Juselius Test Results.

Trace Test										
Pro.		Critical Value 1%		Critical Value 5%		Statistic		Eigen Value		(r)
Gen. dir.	One dir.	Gen. dir.	One dir.	Gen. dir.	One dir.	Gen. dir.	One dir.	Gen. dir.	One dir.	
0.03	0.04	71.48	54.68	63.88	47.86	67.08	48.7	0.58	0.50	No
0.20	0.21	49.36	35.46	42.92	29.80	36.23	23.85	0.49	0.34	At Most 1
0.80	0.39	31.15	19.94	25.87	15.49	12.22	8.79	0.27	0.21	At Most 2
1.00	0.66	16.55	6.63	12.52	3.84	1.03	0.19	0.03	0.01	At Most 3
Maximal Eigen value Test										
0.07	0.11	37.49	32.72	32.12	27.58	30.85	24.86	0.58	0.50	No
0.09	0.28	30.83	25.86	25.82	21.13	24.01	15.06	0.49	0.34	At Most 1
0.49	0.32	23.98	18.52	19.39	14.26	11.18	8.59	0.27	0.21	At Most 2
1.00	0.66	16.55	6.63	12.52	3.84	1.03	0.19	0.03	0.01	At Most 3

Source: Prepared by the researcher based on the outputs of the EViews program.

4.3. Error Correction Model Estimation Results

The ECM is based on the assumption that there are two types of relationship between real GDP and its determinants, a long-run equilibrium relationship and a short-run dynamic relationship. The short-run relationship reflects the immediate or direct relationship which is established between the rate of growth of real GDP and its determinants within the same period, and this is measured in terms of the changes that take place in these variables within each period (Athey et al., 2020; Brynjolfsson et al., 2018; Paltasingh & Goyari, 2013).

Once the error correction model has been estimated, the null hypothesis that there is no causal relationship between the model's variables is tested against the alternative hypothesis that there is a causal relationship. The value of the t-statistic of the coefficient of the lagged error correction term is used to test the long run causality between the variables. The F-statistic value for the independent variables in the error correction equations is used to detect the short-run relationship between the variables. Cointigrants were found for real GDP, artifical intelligence, the growth of real capital accumulation, and the grow of the labor force and therefore, error correction equations were estimated for these variables. The estimation results are given in Table 5.

Table 5: Causality Test Results Using Error Correction Models.

Estimated regression equation	t-value	Pro.	t-value	Pro.	slowdown period	Direction of causality
	Short Run		Long Run			
The equation of the change in the logarithm of real GDP and AI						
D(logY)=D(logR)	2.15	0.11	2.43	0.02	(1)(1)	D(logY) … D(logR)
D(logR)=D(logY)	2.50	0.08	-2.39	0.02	(1)(1)	D(logR) … D(logY)
The equation of the change in the logarithm of real GDP and labor supply						
D(logY)=D(logL)	1.34	0.28	1.91	0.06	(1)(1)	D(logY) …. D(logL)
D(logL)=D(logY)	2.71	0.06	2.62	0.01	(1)(1)	D(logL) …. D(logY)
The equation of the change in the logarithm of real GDP and real capital accumulation						
D(logY)=D(logK)	2.88	0.05	-2.87	0.01	(1)(1)	D(logY) … D(logK)
D(logK)=D(logY)	0.58	0.63	0.27	0.79	(1)(1)	D(logK) … D(logY)

Source: Prepared by the researcher based on the outputs of the EViews program.

Table 5 displays the long run and short run causality between the actual GDP and its determinants. With respect to causality between real GDP and artificial intelligence; the Statistics value of test for coefficient of error correction term is significant at the 2% level in both equation for real GDP and equation for artificial intelligence. This reflects a long-run dual causal relationship, real GDP affects artificial intelligence and artificial intelligence affects the real GDP. Additionally, the estimated F-statistc is insignificant at the 1% level in both the equation for the change in the growth rate of real GDP and the equation for the change in AI. This means that it can be said that there is no short-run causality. In other words, the growth of real GDP does not lead to growth of artificial intelligence, and growth of artificial intelligence does not lead to growth of real GDP in the short run. Hence, the causality between artificial intelligence and real GDP growth is bidirectional in the long-run, and no causality runs between them in the short-run. The results for testing for causality between real GDP and the labor force in Table (5) suggest that the test statistic value for the coefficient of the lagged ecm in the equation explaining the change in growth rate of real GDP is not statistically significant, but it is statistically significant in the equation for the change in the log of labor supply. This is indicative of a one-way long-run causal relationship from real GDP to labour supply. Moreover, the estimated F-statistic is not significant in either the real GDP change or the labour supply change equation. Thus, in the long-run, there is a unidirectional causality running from real gdp to labour supply.

With the respect to the causality from real GDP and real capital accumulation, while the statistically significance value of the coefficient of the lagged error correction term (table 5) of the test statistic is at 1 percent level, hence, calculated F-statistic value reported is significant at 5 percent level in the equation of the change of real GDP. This implies long-run and short-run causality running in one direction from real capital accumulation to real GDP. That is to say, the causal relationship of real GDP with real capital formation is one-way in the long run and one-way in short term. The results are shown in

Table (6).

Table 6: Results of the Error Correction Model.

Real GDP growth does not cause AI growth. AI growth does not cause real GDP growth.	No causal relationship.	short term	direction of causality	Real GDP and AI
Real GDP growth drives AI growth, and AI growth drives real GDP growth.	bidirectional	long term		
Labor force growth does not cause real GDP growth, and GDP growth does not cause labor force growth in the short term.	No causal relationship.	short term	direction of causality	Real GDP and Strong Labor Force
Real GDP growth causes long-term labor force growth	Unidirectional	long term		
Real investment spending causes real GDP in the short term.	Unidirectional	short term	direction of causality	Real GDP and real investment spending
Real investment spending causes real GDP in the long term.	Unidirectional	long term		

5. CONCLUSION

The main purpose of this paper is to explore the cause-and-effect relationship between EXPEND and EEXPEND in the Egyptian economy. The study, through which this would be realised, was put together in seven parts including this introduction. Part two: Literature review and part three: The potential and challenges of artificial intelligence and part four: Profiles of global markets for emerging artificial intelligence companies, part five: Egypt's artificial intelligence landscape, part six: Model were provided in addition to part seven: Methodology as well as the last part: Conclusion and recommendations.

Section 2 presented existing studies and it was clear that, despite the many studies on AI and economic development, no clear conclusion appears to have been drawn. The study also discussed the potentials and challenges of artificial intelligence, and stressed the fact that it is essential to explore these potentials and turn challenges into new opportunities. In addition, the research paper also described the overall image of the worldwide emerging artificial intelligence market in terms of the quantity of artificial intelligence companies and the amount of private investment in the world and the worldwide artificial intelligence market size index. It also highlighted Egypt's endeavors in the domain of artificial intelligences.

In part three we introduced the model of the study by employing the use of Cobb Declauses function form to depict the link between AI and Economic growth as pointed out by earlier work. The methodology and results of the study were in part seven. Depending on the used methodology, unit root and cointegration tests, as well as an error correction models, three types of tests were applied. Unit root tests were employed to check the stationarity of the time series and although several unit root tests are available, two tests, namely the Dickey-Fuller test and the Phillips-Perron test, commonly used in standard econometric research respectively were used in the current study. The degree of cointegration between the growth of real GDP and its determinants was examined.

The study indicates that in the short run, there is a reciprocal relationship between artificial intelligence (AI) growth and real GDP growth—each one influences and drives the other. In contrast, the relationship between real GDP and labor supply is one-way in the long run, with real GDP growth leading to increases in labor supply. Additionally, the theoretical model suggests that long-term causality runs from real investment expenditure to real GDP, meaning investments help drive economic growth over time.

Based on these findings, the study recommends focusing on harnessing AI for economic growth. This involves prioritizing the integration of AI into the economy and society, recognizing AI as a critical driver of development and growth. Emphasizing AI adoption and innovation is key to fostering sustained economic progress.

Maintaining digital transformation: Continued help for digital transformation projects is essential.

AI-Customised Law Making: The report suggests drafting and enacting the appropriate laws related to

AI.

Funding the Use of AI Appropriately The first required action is ensuring funding is available to enable effective use of AI.

Investment in Human Capital for AI: The other side of the argument is that capital and human intellect that can be invested in human development can help co-ordinate AI use sectors of the economy.

Promote International Cooperation on AI Investment: The paper recommends that the governments of developing countries work together to promote AI investment and to also provide the investment in the form of resources that is needed for this to succeed.

Maximising the Opportunities from AI and Addressing the Challenges: Governments are recommended to concentrate on capitalising on the opportunities offered by AI and being proactive in the face of the challenges brought by AI.

Directions for Future Research: The paper suggests that future research can benefit from more updated data or different measurement approaches like VAR.

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