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THE FUNCTIONAL AND INVESTMENT ROLE OF ARTIFICIAL INTELLIGENCE IN THE FINANCIAL SECTOR

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ABSTRACT

The study aims to shed light on the applications and impact of artificial intelligence in the field of financial operations (my usage – investment), by examining the effect of this variable on the current financial industry and its role in enhancing the value of technology companies that choose to invest in it. To achieve the study's objectives, the Autoregressive Distributed Lag (ARDL) model was used over the period from March 2019 to June 2025 on key indicative metrics. The study concluded that there is a weak transitional effect in the extension of the equilibrium relationship from the short term to the long term between the use and development of artificial intelligence, represented by the STOXX Global AI Innovators index, and the AltFi Fintech financial index. It was also found that investment in artificial intelligence technologies (through the STOXX Global AI Innovators index) significantly influences the increase in market value of technology companies listed on the Nasdaq Composite index, regardless of the investment horizon. The study, therefore, recommends periodic evaluations of the effects and integration of AI in both micro and macro finance.

1 INTRODUCTION

The financial sector is one of the fields that has witnessed numerous rapid and significant developments in recent decades. Within this context, innovation has played a fundamental role in driving these changes, contributing to the provision of a diverse range of emerging financial products and technologies. These include enhancing operational and employment capacities through technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) in the modern financial industry. As a result, the financial application and utilization of AI in this field have taken successive strides in their current direction, aiming to create value stemming particularly from smart innovations. Based on the above, the following research question (RQ) can be posed:

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RQ: To what extent can the use and investment in artificial intelligence affect the financial sector?

1.1 Studying Importance and Objectives

The current phase is witnessing modern trends toward the application of artificial intelligence in the financial sector, where the integration and adaptation of the financial industry with what is known as the Fourth Industrial Revolution has opened wide horizons for specialists to explore approaches to using AI technologies in the field of finance and business. This highlights the significance of the profound transformations that have affected the financial industry. Therefore, the research aims to address various aspects related to the development of AI applications and their impact on current financial transactions.

1.2 Study Methodology

This topic was addressed using the descriptive analytical method to review and analyze the most significant developments in the investments and applications of artificial intelligence in the financial sector. Additionally, an empirical study was conducted using several indicators that support this theme, aiming to highlight the impact of AI applications and investment in their technologies within the financial field.

1.3 Study Hypotheses

To address the research question of this study, the following hypotheses (H) were formulated:

H_1: There is a transitional impact of the use of artificial intelligence in the financial sector, from the short to the long term.

H_2: Investment in artificial intelligence technologies has an impact on increasing the market value of major technology companies, regardless of the investment horizon.

2 THE USE OF ARTIFICIAL INTELLIGENCE IN FINANCE

Artificial intelligence-based technologies offer numerous opportunities for the financial sector, witnessing unprecedented growth in recent years within the contemporary financial industry, extending into both traditional and modern financial channels.

2.1 The Concept of AI

Artificial intelligence is the simulation of human intelligence and an attempt to understand its nature through the functioning of computer programs (Majed, 2018). It is the ability to replicate human behavior, thought processes, and working patterns, such as learning, thinking, and exploration (*Artificial Intelligence*, 2021). The use of artificial neural networks allows data analysis, trend and pattern recognition, and the extraction of fundamental rules (Al-Suhayti, 2024). In other words, it embodies the machine's ability to simulate the human mind in how it operates, thinks, discovers, and learns from past experiences (Osoba & Welser IV, 2017).

2.2 The Fourth Industrial Revolution and AI

The Fourth Industrial Revolution was built upon the foundations and principles of the Third Industrial Revolution, particularly through the advancement of emerging technologies. It is characterized by the integration of physical, biological, and digital technologies, alongside the use of artificial intelligence and the application of nanotechnology (Bourana & Benechick, 2022). In other words, it refers to systems of electronically controlled machines (smart machines connected to the Internet) and is often described using terms such as the Digital Industrial Revolution, the Artificial Intelligence Revolution, and the Internet of Things Revolution (Baadi, 2022).

- **The Fourth Industrial Revolution (early 21st century):** It has relied on the outcomes of internet applications, the development of remote sensing devices, 3D printing, smart robotics, emerging digital technologies, autonomous vehicles, nanotechnology, biotechnology, materials science, energy storage, quantum computing, and creative computers (*The Future of Knowledge : A Foresight Report 2019*, 2019).
- **The shift of major economies toward the Made in strategy:** The Fourth Industrial Revolution has led many major economies to develop long-term strategies to achieve their intended goals (i.e., the Fourth Technological Revolution). As a result, the Made in strategy for the said countries has gained significant importance. For example, in 2015, during its

12th Five-Year Plan, China launched the Made in China 2025 strategy ("Made in China 2025," 2018). This plan is like Germany's Industry 4.0 strategy adopted in 2012, Japan's plan from 2015, and France's Industry of the Future initiative launched in 2015 (Goulard, 2017), all of which aim to take the lead in innovation. In recent decades, the goal of dominant and emerging economies to control global wealth has increasingly relied on expanding their investments in smart technologies (Arora & Vamvakidis, 2010).

2.3 The International Investment in AI

Global investments in the field of artificial intelligence have achieved numerous promising indicators. According to the International Data Corporation (IDC), global spending on AI alone reached $19.1 billion by the end of 2018, an increase of 54.2% compared to 2017, and rose to $52.2 billion in 2021, recording a compound annual growth rate (CAGR) of 46.2%. Currently, the retail sector is the highest spender on AI, followed by the financial sector (Studies and Research Department, 2021).

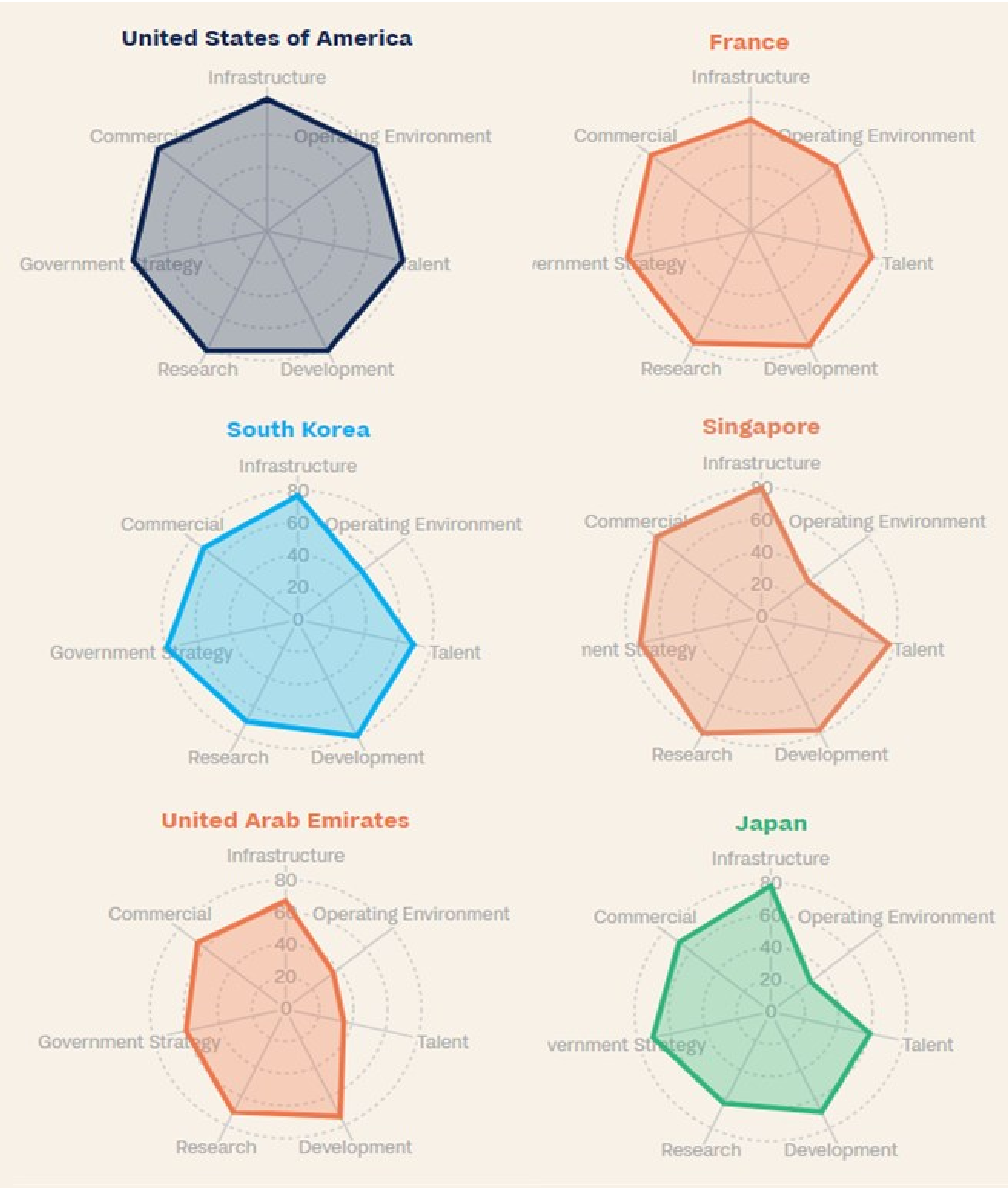

***Figure 1a**. Global Index on Responsible AI: 2024 scores*

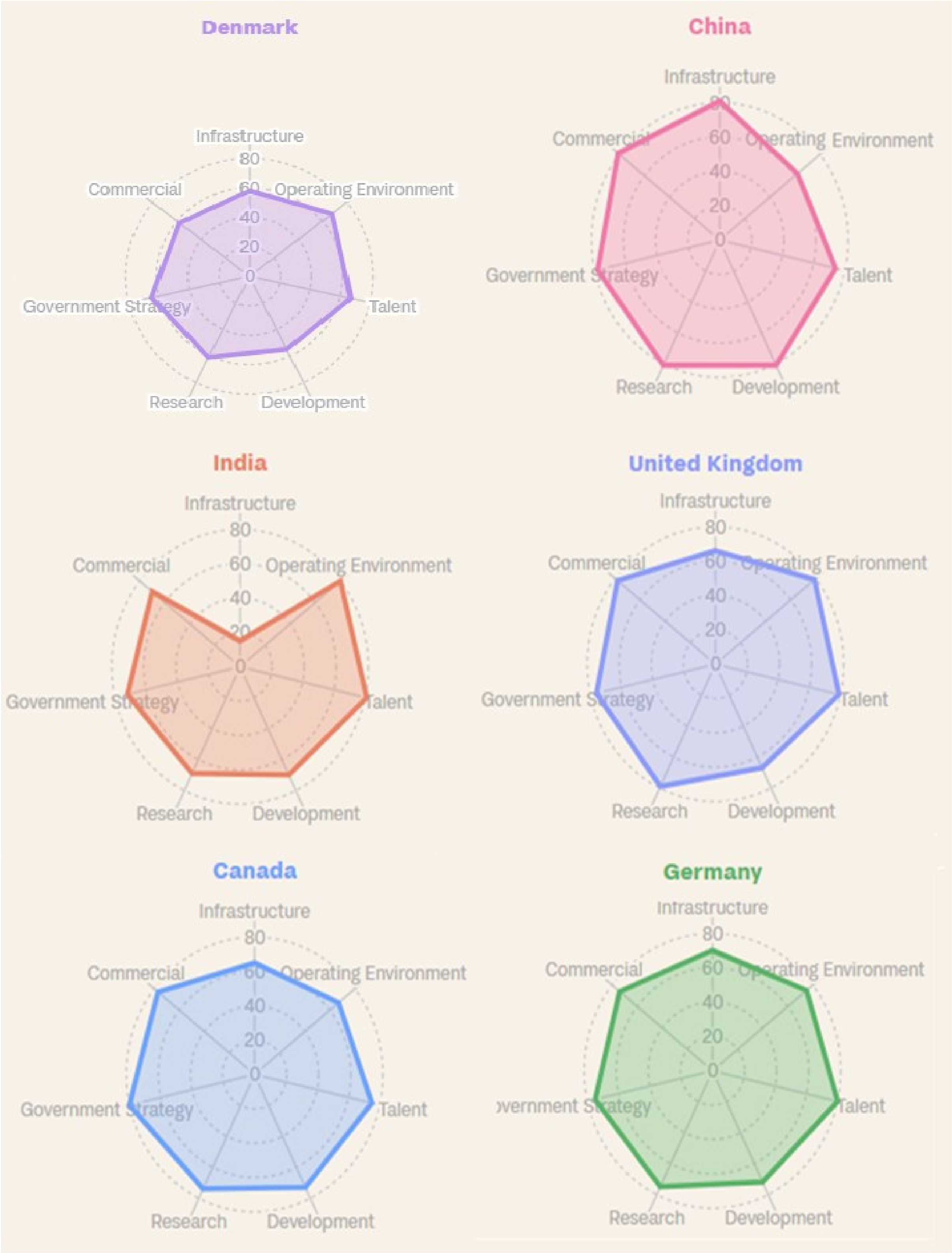

***Figure 1b**. Global Index on Responsible AI: 2024 scores*

Source: (The Global AI Index, n.d.).

In 2024, private investment in AI in the United States rose to $109.1 billion, nearly 12 times that of China ($9.3 billion), and 24 times that of the United Kingdom ($4.5 billion). Notably, generative AI witnessed particularly strong momentum, attracting $33.9 billion in private global investments, an 18.7% increase compared to 2023. AI adoption in the business sector is also accelerating, with 78% of companies using AI in 2024, marking a 55% increase from the previous year. The chart (Figures 1a and1b) highlights the leading countries focusing on investment in this field (Human-Centered Artificial Intelligence (HAI), 2025).

The Global AI Index for 2024 presents the level of advancement among leading economies that are actively engaged in AI applications, based on the following criteria: infrastructure, trade, government strategy, research, growth, talent, and operating environment. According to the index, the United States, China, Germany, France, Canada, and the United Kingdom ranked highest across these indicators. However, as technological progress, particularly in artificial intelligence (AI) continues to reshape societies, its impact on economic activities, markets, and social structures has begun to create significant challenges for policymakers, especially amid rising international investment in this field (Saba & Pretorius, 2024).

2.4 AI Applications in the Financial Sector

The use of artificial intelligence technologies is generally beneficial for companies. On one hand, AI as a potentially general-purpose technology can stimulate the growth of firms and institutions by fostering process innovation or product innovation, which are two complementary channels. Through cost reduction, innovation, expansion, and product diversification, AI becomes a vital mechanism for the economic, commercial, and financial growth of companies and institutions, Babina et al. (2023).

On the other hand, the specific applications of AI in the financial sector are numerous and include fintech and blockchain technologies, market operations, pricing decisions, and hedging, smart customer interaction and demand forecasting, fraud and scam detection, risk assessment and pricing of insurance contracts through complex algorithms that leverage real-time data and developments, investment management, back testing and simulation of financial instruments before their market release (Studies and Research Department, 2021).

In this regard, an important concern arises around the evaluation of AI methods used by asset management firms, which require reliable forecasting tools for making investment decisions. Financial authorities and supervisory bodies also share this concern and researchers, who need to understand how markets function by incorporating these emerging methods (Giudici & Raffinetti, 2023).

2.5 FINTECH AND AI

Fintech can enhance the financial services industry in many ways, more broadly, fintech is likely to have a greater systemic impact through key transformational mechanisms, such as the disintermediation of incumbents, disaggregation of financial services and decentralization of networks (*Fintech and Financial Stability*, 2017). As a result, artificial intelligence and financial technology (FinTech) are seen as powerful forces capable of transforming the structure of future financial services, given that FinTech blends innovation with emerging technologies and integrates AI into financial activities (Saad Guermech, 2025). AI enables lower operational costs, improves the performance of financial institutions, and enhances their profitability. This is why many institutions are pursuing this new direction. According to PwC, AI is expected to contribute around $15.7 trillion to the global economy by 2030, including $6.6 trillion from increased productivity and $9.1 trillion from higher consumption driven by improved product quality worldwide an amount equivalent to ten times the value of global oil sales (Majed, 2018).

3 AN ECONOMETRIC STUDY ON: STOXX G. AI. I, ALTFI, AND NASDAQ

The econometric study examines the impact of artificial intelligence usage on both employment-related and investment-related aspects within the financial sector. This is done by analyzing the financial values of the following indices: STOXX Global AI Innovators, AltFi Fintech, and Nasdaq Composite, over the period (03/2019–06/2025), with values assessed in U.S. dollars.

These indices were selected as they serve as indicators for various variables that align with the objectives of the study. the table1 represents the selected financial indicators used in the study.

***Table 1**. Definition of study indicators*

The indicator	The definition
STOXX Global AI Innovators (European)	The index monitors the performance of a group of companies considered major contributors to the development of artificial intelligence. It includes around 200 companies from a wide range of sectors that heavily invest in AI technologies, including Apple, Deutsche Telekom, Bank of America, and Facebook. The new STOXX AI Index selects its components using AI technology, making it the first objective index to do so. STOXX collaborated with Yewno, an award-winning AI company, in its creation. The index's composition is based on the STOXX Global Index and the Developed Markets Index, which together track around 7,000 stocks (Deutsche Boerse Group, 2025).
AltFi Fintech (German)	The index is rule-based and tracks the market performance of a selected group of global companies listed on international stock exchanges. These companies benefit from disruptive innovations in financial products and services and utilize emerging technologies that affect the strategies and structure of traditional financial sector markets. The index components are weighted using a modified free-float market capitalization algorithm (BITA, 2023).
Nasdaq Composite (American)	The Nasdaq Composite Index is a composite index that includes over 3,000 listed companies and is considered one of the most closely followed indices worldwide. It comprises both U.S. and non-U.S. companies, with some of the largest listed firms being Apple, Amazon, Microsoft, and others. Each stock's weight in the index is calculated based on its market capitalization, and the index is commonly used as a benchmark for the performance of technology company stocks (Aoun Allah, 2025).

Source: Prepared by the author.

3.1 Study Tools and Tests

The Autoregressive Distributed Lag (ARDL) model was applied to the financial values of the variables during the study section, to determine the nature of the relationship between them, allowing for achieving the desired results using the 10Eviews program.

3.2 Autoregressive distributed lag model (ARDL)

By relying on the frontier approach to joint integration, which is based on the autoregressive distributed lag (ARDL) model developed by Pesaran et al (2001), and based on the study variables, the logarithmic model can be formulated according to the following relationship:

$$In\ (S) = \beta_0 + \beta_1\, In(N) + \beta_2\, In(T) + \varepsilon_t$$

$$\Delta\,(InS)_t = \beta_0 + \beta_1\,(In\ S)_{t-1} + \beta_2\,(InN)_{t-1} + \beta_3\,(InF)_{t-1} + \sum_{t=1}^{p} \beta_1\,\Delta\,(In\ S)_{t-1} + \sum_{t=1}^{p} \beta_2\,\Delta\,(InN)_{t-1}$$
$$+ \sum_{t=1}^{p} \beta_3\,\Delta\,(InF)_{t-1} + \Psi\,(ECT)_{t-1} + \varepsilon_t$$

Where:
Δ: the first difference,
ε_t: Random error term
s: Monthly returns of the STOXX Global Artificial Intelligence Innovators Index
N: Monthly returns of the Nasdaq Composite Index
F: Monthly returns of the AltFi Fintech Index
$(ECT)_{t-1}$: Error correction term

This formulation is used to verify the existence of cointegration or a long-term relationship between the study variables, Breshi et al. (2020).

3.3 Study of Stability

The financial values are considered during the study period, as shown in the following figures, to test their stability:

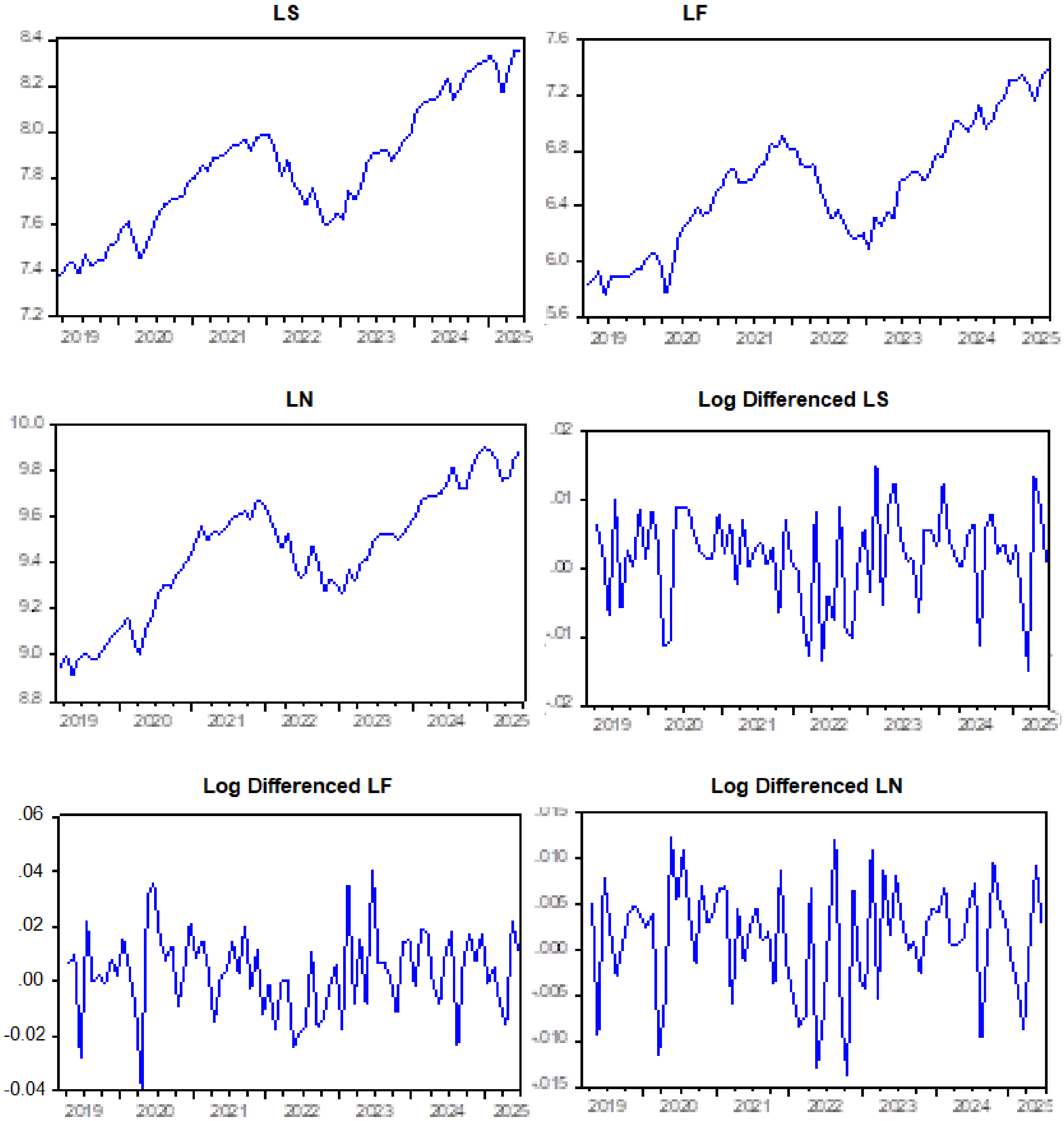

***Figure 2**. Financial values of the study variables during the period: (03/2019-06/2025)*
Source: Prepared by the author based on the outputs of EViews 10.

Figure 2 shows a pattern of significant ups and downs in the financial returns of the indices during the study period. Notably, sharp declines occurred in 2020 across all variables, which can be attributed to the health crisis period marked by strict lockdown measures that affected nearly all sectors, especially industry, and had a notable impact on global stock markets overall. Despite the gains made by major technology companies during that time, investment uncertainty dominated pricing movements in most sectors (except for investments in the healthcare sector). The Nasdaq Index also recorded significant losses in 2022, driven by concerns over inflation and rising interest rates. Similarly, the years 2024 and 2025 saw sharp declines as well, following. disappointing earnings reports from some major tech companies. As shown in Figure 2, the Artificial Intelligence Index (S) and the Fintech Index (F) followed similar waves, though with less intensity, given that these indices are influenced by the financial and investment activity of major technology firms.

3.4 Stability Test

To test the stability of the financial value series, the Augmented Dickey-Fuller (ADF) test will be applied. The ADF formulation involves adding lagged differences s_{t-j+1} to address the problem of autocorrelation among values (Meziene, 2019), Additionally, the Phillips-Perron (PP) test will be used due to its higher accuracy. Phillips and Perron developed a generalization of the Dickey-Fuller method that accounts for conditional heteroskedasticity in the error terms, which the ADF test does not address (Delmi & Zeghoudi, 2021). After conducting the tests on the study variables, the results were obtained as shown in Table 2.

***Table 2**. Unit root test results*

Variables	Unit root test results at the level and first-order differences (D)					
	A Dickey-Fuller					
	constant only		constant and trend		Without constant and trend	
	t-Statistic	Prob	t-Statistic	Prob	t-Statistic	Prob
LS	-0.698839	0.8402	-1.68674	0.7476	2.06791	0.9904
D- LS	-8.908109	0	-8.85570	0	-8.49794	0
LF	-0.613274	0.8606	-1.57218	0.7947	1.81739	0.9827
D- LF	-8.806685	0	-8.76038	0	-8.47581	0
LN	-1.138966	0.6963	-1.84653	0.672	1.84655	0.9838
D- LN	-8.544264	0	-8.48359	0	-8.24785	0
Variables	Phillips-Perron					
	constant only		constant and trend		Without constant and trend	
	t-Statistic	Prob	t-Statistic	Prob	t-Statistic	Prob
LS	-0.698839	0.8402	-1.70082	0.7413	2.067913	0.9904
D- LS	-8.908109	0	-8.8557	0	-8.50017	0
LF	-0.594123	0.8649	-1.56977	0.7956	1.849997	0.984
D- LF	-8.806658	0	-8.7604	0	-8.47558	0
LN	-1.106621	0.7094	-1.84653	0.672	1.99092	0.9884
D- LN	-8.559311	0	-8.4947	0	-8.24785	0

Source: Prepared by the author based on the outputs of EViews 10.

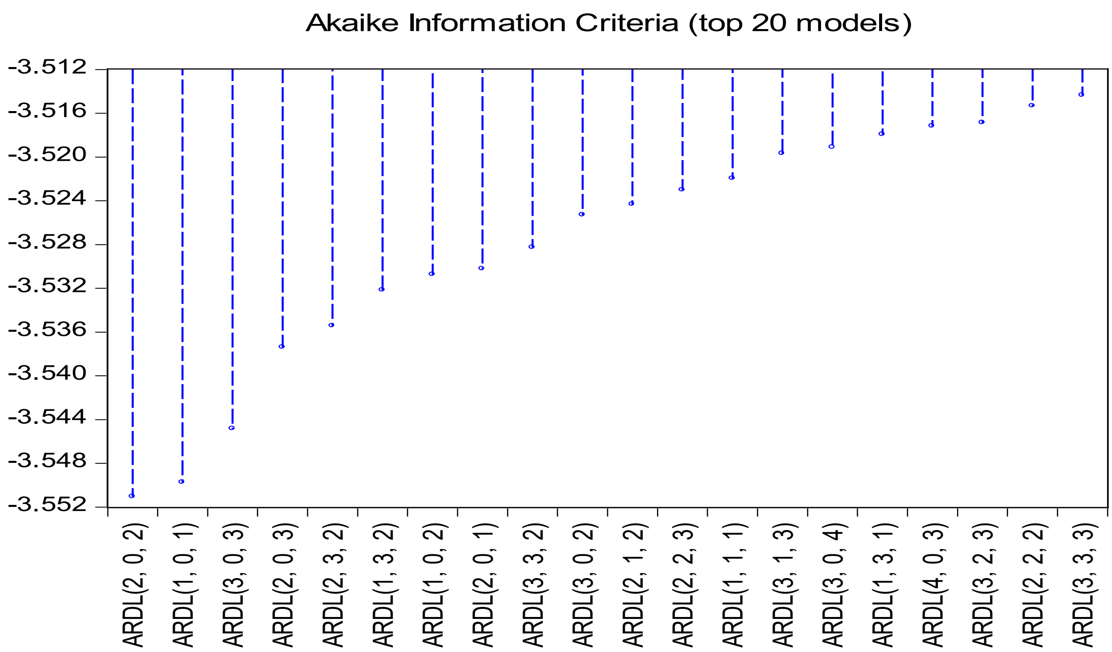

***Figure 3**.Optimal lag length of the model according to the Akaike Information Criterion (AIC)*

Source: Prepared by the author based on the outputs of EViews 10.

Based on the test results (Table 2), it was found that the value series were not stationary at the level. Therefore, first-order differencing was applied in both the ADF and PP tests for the study variables. The results confirmed that all variables became stationary at first difference in the case of a constant, a constant and a trend, and without a constant or trend. The p-values presented in the table show the outcomes of the tests performed.

3.5 The Optimal Lag Length

To determine the optimal lag length for the studied variables, the Akaike Information Criterion (AIC) was used, as illustrated in Figure 3.

The optimal lag lengths for the ARDL model were determined according to the Akaike Information Criterion (AIC) as (2, 0, 2).

3.6 Testing the Goodness of Fit of the ARDL Model

To determine the suitability of the ARDL model, a model compatibility test was conducted with the study sample, and the results were: the R-squared value was 0.979416, and the F-statistic was 531.3304, with a p-value less than 0.00001, indicating a high level of statistical significance. These results confirm that the model is suitable for further analysis, as shown in Table 3.

Table 3: *ARDL model*

Dependent Variable: LS				
Method: ARDL				
Date: 11/22/25 Time: 12:08				
Sample (adjusted): 2019M05 2025M06				
Included observations: 74 after adjustments				
Maximum dependent lags: 4 (Automatic selection)				
Model selection method: Akaike info criterion (AIC)				
Dynamic regressors (4 lags, automatic): LF LN				
Fixed regressors: C				
Number of models evalulated: 100				
Selected Model: ARDL(2, 0, 2)				
* *Note: final equation sample is larger than selection sample*				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
LS(-1)	0.553182	0.126862	4.360500	0.0000
LS(-2)	0.215113	0.125895	1.708661	0.0921
LF	0.095352	0.068697	1.388010	0.1697
LN	0.578458	0.104400	5.540781	0.0000
LN(-1)	-0.272676	0.129968	-2.098020	0.0397
LN(-2)	-0.228875	0.113650	-2.013861	0.0480
C	0.471919	0.554905	0.850449	0.3981
R-squared	0.979416	Mean dependent var		7.857453
Adjusted R-squared	0.977573	S.D. dependent var		0.266353
S.E. of regression	0.039888	Akaike info criterion		-3.515658
Sum squared resid	0.106601	Schwarz criterion		-3.297706
Log likelihood	137.0793	Hannan-Quinn criter.		-3.428714
F-statistic	531.3304	Durbin-Watson stat		2.043098
Prob(F-statistic)	0.000000			

* *Note: p-values and any subsequent tests do not account for model selection.*

Source: Prepared by the author based on the outputs of EViews 10.

3.7 Diagnostic Tests of the Model

The Breusch–Godfrey Serial Correlation LM test was employed to examine whether the error terms in the regression model are independent or exhibit serial correlation. This diagnostic procedure is essential for assessing the validity of the model's assumptions regarding the independence of residuals. In addition, a heteroskedasticity test was conducted to evaluate whether the variance of the residuals remains constant or varies systematically with the independent variables. The outcomes of these diagnostic tests are presented below.

3.7.1 Breusch-Godfrey Serial Correlation LM Test

***Table 4**.Test of Multicollinearity in the Model*

Breusch-Godfrey Serial Correlation LM Test:	
F-statistic	1.037449
Obs*R-squared	2.289120
Prob. F(2,65)	0.3601
Prob. Chi-Square(2)	0.3184

Source: Prepared by the author based on the outputs of EViews 10.

Based on the results of the Breusch-Godfrey Serial Correlation LM Test, the null hypothesis (H_0), which states that there is no autocorrelation among the residuals, is accepted, since the p-value is greater than 5%.

3.7.2 *Heteroskedasticity Test*

***Table 5**. Results of the Heteroskedasticity Test Based on Linear Regression*

Heteroskedasticity Test:	
F-statistic	1.597650
Obs*R-squared	1.606505
Prob. F(1,71)	0.2104
Prob. Chi-Square(1)	0.2050

Source: Prepared by the author based on the outputs of EViews 10.

Given that the p-value of the Chi-Square test statistic (df = 1) exceeds the 5% significance level, the null hypothesis (H_0) cannot be rejected. Consequently, the alternative hypothesis (H_1), which posits the presence of heteroskedasticity in the residuals, is not supported.

3.8 Estimates of Normality Test

JB is asymptotically chi-squared distributed with two degrees of freedom because JB is just the sum of squares of two asymptotically independent standardized normals (Thadewald & Büning, 2004). In other words, the Jarque-Bera statistics must be statistically insignificant at the 5% level for the null hypothesis of normality to be accepted (Naas, 2023).

Upon applying for the test, the results were as follows (see figure 4):

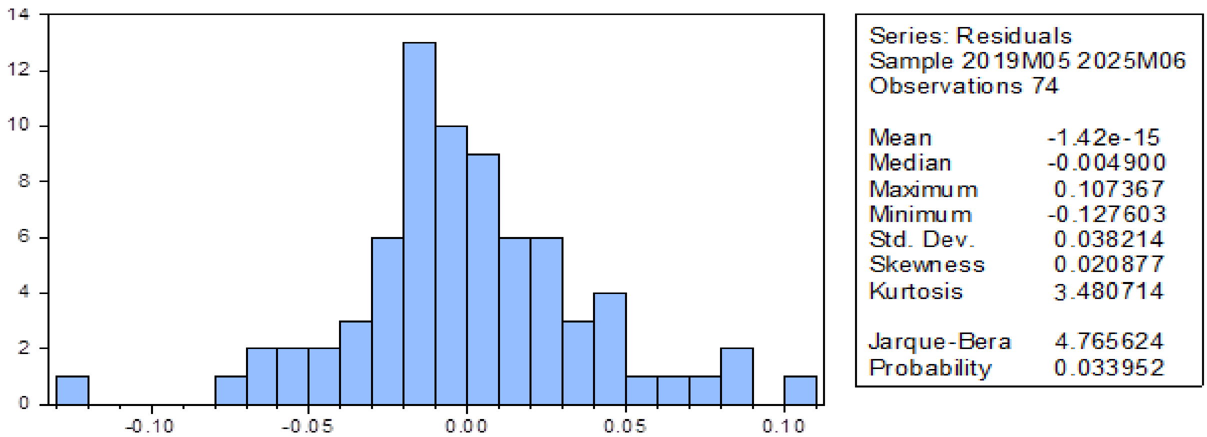

***Figure 4**. Results of the Normality Test*
Source: Prepared by the author based on the outputs of EViews 10.

Based on the test output, it is evident that the residual values follow a normal distribution, which supports the null hypothesis of normality at the 5% significance level. This is further confirmed by the calculated Jarque-Bera statistics of (4.76), which is less than the critical value of (5.99), in addition to a p-value greater than 5%.

3.9 Bounds Test for Cointegration

According to Pesaran et al. (2001), cointegration in the ARDL model is determined as follows: If the calculated F-statistic is greater than the upper critical bound, the null hypothesis of no cointegration is rejected; if the F-statistic is less than the lower critical bound, the null hypothesis is accepted, indicating no cointegration. However, if the F-statistic lies between the lower and upper critical bounds, no conclusive decision can be made (Eschouf, 2024).

The F-statistic was calculated as 4.904119, which exceeds the I(1) critical bound values at the 10% and 5% significance levels. This indicates the presence of a long-term cointegrating relationship from the short term to the long term at these levels. Therefore, the null hypothesis of no cointegration between the variables is rejected, and the alternative hypothesis, which suggests the existence of cointegration between the Artificial Intelligence Index (S), the Nasdaq Composite Index (N), and the Fintech AI Index (F), is accepted.

***Table 6**. Results of the ARDL Bounds Test for Cointegration*

ARDL Bounds Test		
Date: 11/22/25 Time: 12:32		
Sample: 2019M05 2025M06		
Included observations: 74		
Null Hypothesis: No long-run relationships exist		
Test Statistic	**Value**	**k**
F-statistic	4. 908095	2
Critical Value Bounds		
Significance	**I0 Bound**	**I1 Bound**
10 %	3.17	4.14
5 %	3.79	4.85
2.5%	4.41	5.52
1 %	5.15	6.36

Source: Prepared by the author based on the outputs of EViews 10.

***Table 7**. Results of the Short-Run and Long-Run Relationships in the ARDL Model*

ARDL Cointegrating and Long Run Form				
Dependent Variable: LS				
Selected Model: ARDL(2, 0, 2)				
Date: 11/22/25 Time: 12:34				
Sample: 2019M03 2025M06				
Included observations: 74				
Cointegrating Form				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LS(-1))	-0.215113	0.125895	-1.708661	0.0921
D(LF)	0.095352	0.068697	1.388010	0.1697
D(LN)	0.578458	0.104400	5.540781	0.0000
D(LN(-1))	0.228875	0.113650	2.013861	0.0480
CointEq(-1)	-0.231706	0.115756	-2.001674	0.0494
Cointeq = LS - (0.4115*LF + 0.3319*LN + 2.0367)				
Long Run Coefficients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LF	0.411522	0.235783	1.745345	0.0855
LN	0.331918	0.396117	0.837930	0.4050
C	2.036714	2.253956	0.903617	0.3694

Source: Prepared by the author based on the outputs of EViews 10.

3.10 Estimating the Short- and Long-Run Relationship

Based on the test outputs, it was found that a one-unit change in the price of the Artificial Intelligence Index (S) leads to a change of 0.09 units in the Fintech Index (F) in the same direction. While the impact is relatively weak, it is still acceptable, as it approaches 10%, and it aligns closely with the findings of the Artificial Intelligence Index Report 2025 published by the Stanford University AI Center (See report: Human-Centered Artificial

Intelligence (HAI), 2025), regarding the adoption of AI in financial technology. This result can be objectively explained, as the Fintech Index (F) captures a wide range of macro-financial variables, including: the performance of major publicly listed companies, innovation in financial services, and emerging technologies affecting the traditional financial sector. These components provide a reasonable interpretation of the estimated coefficient. Furthermore, the use of artificial intelligence in the financial sector is relatively recent, compared to previous financial and technological innovations, and the traditional financial sector remains less flexible in responding to such innovations at this stage, due to the persistence of conventional and trusted products and structures. Also, AI applications in finance are still hard to quantify in many of their forms.

As for the Nasdaq Composite Index, every one-unit increase in the AI Index (S) leads to a 0.57 unit increase in the Nasdaq, which is a very strong effect. This indicates that investment in AI significantly boosts the value of major technology companies listed in the index. It reflects the current investment trend in this sector, which exerts a compound effect on tech companies through both usage and investment in AI technologies.

Regarding the error correction rate from short-run imbalances toward long-run equilibrium, the error correction term (ECT) was estimated at – 0.23170), indicating that about 23% of the short-run disequilibrium is corrected toward the long-run relationship in each period.

Considering the p-value, the null hypothesis (H_0) is rejected in favor of the alternative hypothesis (H_1), which confirms the presence of a long-run equilibrium relationship. The direction of this relationship runs positively from the AI Index (S) toward both the Fintech Index (F) and the Nasdaq Composite Index (N).

3.11 Stability Test of the Estimated ARDL Model

The structural stability test shows that the short-run coefficients are stable and consistent with the long-run coefficients. To assess this, the CUSUM test and the CUSUM of Squares test are used.

Structural stability of the estimated ARDL coefficients is confirmed when both tests remain within the critical bounds at the 5% significance level, thereby leading to the acceptance of the null hypothesis of coefficient stability (Bousba & Sahli, 2020). Figures 5 and 6 illustrate the results of these tests.

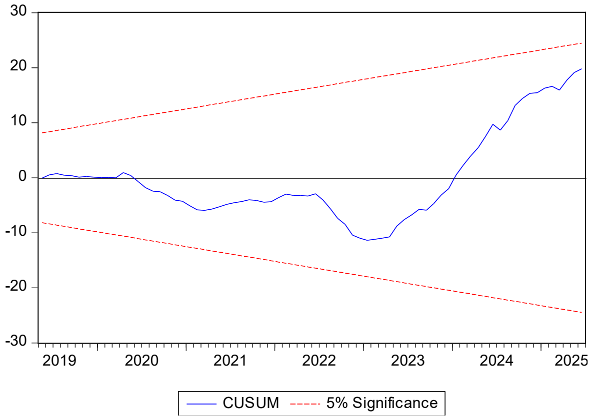

***Figure 5**. Cumulative Sum of Recursive Residuals.*
Source: Prepared by the author based on the outputs of the EViews 10

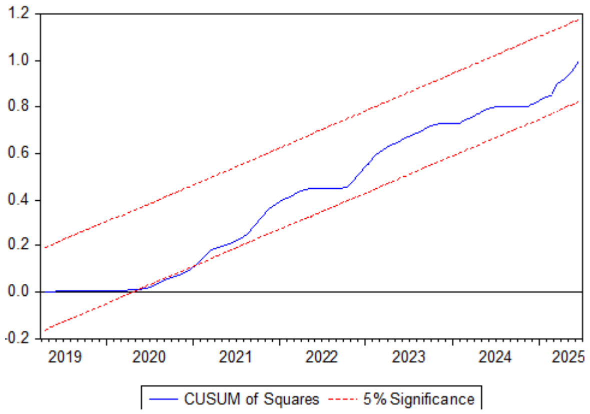

***Figure 6**. Cumulative Sum of Squares of Recursive Residuals*
Source: Prepared by the author based on the outputs of the EViews 10

It is observed from the CUSUM test and the CUSUM of Squares test that both lie within the critical bounds at the 5% significance level. This indicates the stability of the short- and long-run coefficients of the estimated model and reflects consistency between the long-run and short-run results.

4 CONCLUSION

The current phase is marked by pivotal transformations in the field of modern finance, making the rise and expansion of artificial intelligence investments and applications in the financial sector one of its key outcomes. This development calls for broader and more in-depth research by specialists to fully understand the growing impact of emerging smart technologies in the fields of finance and business, an impact that ultimately reflects on the financial sector in one way or another.

This was clearly demonstrated by the findings of the present study on various levels, including traditional, newly emerging, and innovative dimensions, which are summarized as follows:

- There is a transitional effect of artificial intelligence applications in the financial sector from the short term to the long term, which supports the validity of the first hypothesis. Every action generates reactions as a response to changes within a highly sensitive sector. These reactions may unfold over varying time horizons, whether in the short term, over several years, or even decades.
- The statistical results of this study indicate a weak but acceptable long-term equilibrium relationship (with the potential to grow in later phases) between the use and development of AI and its impact on various components such as: The performance of large companies listed on international stock exchanges, innovations in financial services, and the technologies adopted in the traditional financial sector especially given the vast scope of the financial system. The integration of AI into both modern and traditional financial frameworks is still relatively new, especially when compared to earlier technologies like traditional algorithms or human-based data analysis. This novelty limits AI's current long-term impact on macro-finance and raises several concerns among specialists and experts about the potential risks associated with excessive AI use in financial industries. These concerns may explain the cautious approach adopted by key financial market players, particularly those leading the markets, regarding the full integration of AI. Some fear that financial investment could drift too far from traditional foundations, possibly reaching a point beyond human control. Additionally, a noticeable mismatch in the pace between the regulatory/legal frameworks and the rapid adoption of AI in financial systems creates uncertainty. This regulatory lag makes the long-term impact of AI less clear and harder to measure than its short-term effects.
- There is a positive impact of investment in AI technologies on the market values of major tech companies, regardless of the investment horizon, confirming the second hypothesis. The results support this claim, as the interactive and complementary relationship between tech companies listed in the AI Index (S) and the Nasdaq Composite Index (N) creates a dynamic synergy in the overall tech investment landscape. This connection is reflected in the prices of tech assets if investment in AI technologies continues. The largest companies investing in AI are already listed in the Nasdaq, which aligns well with the components of the AI Index (S) an index that monitors the development of AI technologies by leading firms such as: Microsoft Corp., NVIDIA Corp., Meta Platforms Class A, Alphabet Inc. Class A, Marvell Technology, etc. (See: Deutsche Borse Group, 2025). These firms are also listed in the Nasdaq Composite Index, and many of them are actively targeting innovation in the financial sector, among others. Therefore, the study's findings are valid and acceptable at this stage. Since these companies aim to fulfill a smart industrial vision, they view continuous innovation in AI as both a way to boost short-term market value and to ensure long-term expansion of their entities.

The study, therefore, recommends periodic evaluations of the effects and integration of AI in micro and macro finance.

WORKS CITED

Al-Suhayti, H. F. (2024). *Artificial intelligence: its concept and importance in the public financial sector*. Department of Finance: Government of Government, 1-19. https://2u.pw/CvpZu8WC

Aoun Allah, S. (2025). A study on the trend of high-technology sector stocks: A case study of NASDAQ index indicators during the period 2009–2019. *Journal of Economic and Administrative Research*, *15*(1), 157–176. https://asjp.cerist.dz/en/downArticle/101/15/1/153120

Arora, V., & Vamvakidis, A. (2010). *Gauging China's Influence*. Finance & Development, 11-13. https://www.imf.org/external/pubs/ft/fandd/2010/12/pdf/Arora.pdf

Artificial intelligence: Iḍāʾāt. (2021). Institute of Banking Studies, 3-10. https://kibs.edu.kw/wp-content/uploads/2021/10/March-2021-Artificial-Intelligence.pdf

Baadi, A. (2022). The Fourth Industrial Revolution. *Journal of Economics and Sustainable Development*, *5*(2), 561–577. https://asjp.cerist.dz/en/downArticle/598/5/2/200188

Babina, T., Fedyk, A., He, A., & Hodson, J. (2023). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, *151*, 1–15. https://doi.org/10.1016/j.jfineco.2023.103745

BITA. (2023, October 31). *ALTFI Fintech Index*. altfi.com, 1-3. https://assets.ctfassets.net/2chiqpnroeav/1oiTXDOBVxy4gdDXo5IK5G/d63e5d0d967e040f29c37fdc755aeb7b/AltFi_Index_Factsheet__1_.pdf

Bourana, Y., & Benechick, A. S. (2022). Sectoral analysis of small businesses in Arab countries, in light of digital transformation and Industry 4.0 requirements. *Economic Researcher Review*, *10*(2), 325–343. https://asjp.cerist.dz/en/downArticle/85/10/2/210769

Bousba, S., & Sahli, I. (2020). Standard modeling of the impact of financial depth and exchange rate on inflation in Algeria, using self - Autoregressive Distributed Lag Model ARDL during the period 1974 –2018. *The Economic Science, Management and Business Science*, *13*(1), 338–357. https://asjp.cerist.dz/en/downArticle/324/13/1/122456

Breshi, A., Belouafi, M., & Foudou, M. (2020). The impact of financial development and trade openness on economic growth in Algeria during the period 1970-2018. *El-Bahith Review*, *20*(1), 385–399. https://asjp.cerist.dz/en/downArticle/7/20/1/139361

Delmi, S., & Zeghoudi, A. (2021). Return Predictability as one of the Stock Market Anomalies. Case study of Saudi capital market (2007-2017) Using Variance Ratio tests and ARIMA-GARCH model. *Les Cahiers Du MECAS*, *16*(2), 213–231. https://asjp.cerist.dz/en/downArticle/174/16/2/137481

Deutsche Börse Group. (2025). *STOXX Index Methodology Guide*. STOXX.com,1-626. Retrieved November 29, 2025, from https://www.stoxx.com/document/Indices/Common/Indexguide/stoxx_index_guide.pdf

Eschouf, A. (2024). Electrical energy consumption from renewable sources and its relationship to environmental pollution in Algeria during the period (2000-2021). *Economic Researcher Review*, *12*(2), 13–32. https://asjp.cerist.dz/en/downArticle/85/12/2/258027

Fintech and financial stability. (2017). DTCC Group,2-19. https://www.dtcc.com/-/media/Files/PDFs/Fintech-and-Financial-Stability.pdf

Giudici, P., & Raffinetti, E. (2023). SAFE Artificial Intelligence in Finance. *Finance Research Letters*, *56*, 1–14. https://doi.org/10.1016/j.frl.2023.104088

Goulard, S. (2017, December). *China's new trade strategies*, LARITIME - SAINT NAZAIRE,1-4. https://www.isemar.org/wp-content/uploads/2017/12/note-de-synth%C3%A8se-195-Les-nouvelles-strat%C3%A9gies-commerciales-de-la-Chine.pdf

Human-Centered Artificial Intelligence (HAI). (2025). *Artificial Intelligence Index Report 2025*. Stanford University,1-456. https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf

Made in China 2025. (2018). In *www.isdp.eu*. Institute for Security & Development Policy, 1-9. https://www.isdp.eu/wp-content/uploads/2018/06/Made-in-China-Backgrounder.pdf

Majed, A. (2018). *Artificial intelligence in the United Arab Emirates*. Department of Economic Studies and Policies,Ministry of Economy,1-18. https://beta.government.ae/-/media/About-UAE/Strategies/AI-Report-2018.pdf

Meziene, A. (2019). *Economic policies in developing countries between the reality of financial globalization and the requirements of development: the case of Algeria* [Kasdi Merbah University– Faculty of Economic, Commercial and Management Sciences], 2-307.

https://dspace.univ-ouargla.dz/jspui/bitstream/123456789/22910/1/MEZIENE-Abdelghafour.pdf

Naas, S. E. (2023). The dynamic interaction of investor sentiment towards geopolitical risk, economic policy uncertainty, and oil price shocks: evidence from a model augmented ARDL. *Economic Researcher Review*, *11*(2), 111–125. https://asjp.cerist.dz/en/downArticle/85/11/2/235600

Osoba, O., & Welser IV, W. (2017). *The Risks of Artificial Intelligence to Security and the Future of Work*. Rand Corporation,1-23. https://doi.org/10.7249/pe237

Saad Guermech, Z. (2025). The role of financial technology and digital practices in achieving digital financial inclusion in Islamic Banks, with reference to the Malaysian experience. *Economic Researcher Review*, *13*(1), 191–207. https://asjp.cerist.dz/en/downArticle/85/13/1/272179

Saba, C. S., & Pretorius, M. (2024). The impact of artificial intelligence (AI) investment on human well-being in G-7 countries: Does the moderating role of governance matter? *Sustainable Futures*, *7*, 2–19. https://doi.org/10.1016/j.sftr.2024.100156

Studies and Research Department. (2021). *Financial technology and artificial intelligence in the financial and banking sector* (454th ed.). Union of Arab Banks,1-8. https://2u.pw/Mhb2R4

Thadewald, T., & Büning, H. (2004). Jarque-Bera Test and its competitors for testing Normality: A power comparison. *EconStor*, 2–22. https://www.econstor.eu/bitstream/10419/49919/1/668828234.pdf

The Future of Knowledge : A Foresight Report 2019. (2019). Mohammed bin Rashid Al Maktoum Knowledge Foundation,5-305. https://www.undp.org/sites/g/files/zskgke326/files/migration/arabstates/f1a98a318cc5d25e878dafd507657a146b3266d00ecdea9b928c027ad3bd8a30.pdf

The Global AI Index. (n.d.). Tortoise Media. Retrieved November 29, 2025, from https://share.google/BbApgtHiLrFJoCxZn

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