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ARTIFICIAL INTELLIGENCE AND CAPITAL MARKET PERFORMANCE IN NIGERIA: EVIDENCE OF SPILLOVERS FROM THE GLOBAL AI MARKET

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ABSTRACT

This study investigates the effect of Artificial Intelligence (AI) on capital market performance in Nigeria, using the Adaptive Market Hypothesis as its theoretical framework. The study examines whether growth in the global AI market is associated with changes in Nigeria's capital market performance, measured by stock market capitalisation. Secondary annual data were obtained from the World Bank, Central Bank of Nigeria (CBN), National Bureau of Statistics (NBS), and relevant industry reports. To account for potential technology diffusion lags, global AI market size was introduced with a one-year lag. Brent crude oil price, USD/NGN exchange rate, and inflation rate were included as control variables. Pearson correlation and Ordinary Least Squares (OLS) regression were employed for the empirical analysis. The findings indicate that global AI market growth has no statistically significant immediate effect on Nigeria's capital market performance. However, the positive coefficient associated with the one-year lag suggests a potential delayed transmission effect, while the inclusion of macroeconomic controls improves the explanatory power of the model. The findings suggest that the benefits of global AI development may reach Nigeria gradually through channels such as fintech adoption, algorithmic trading, digital financial services, and investor sentiment. The study contributes to the emerging literature by providing empirical evidence on the relationship between global AI market development and Nigeria's capital market performance, thereby extending the discussion of AI and financial markets to an emerging-market context.

***Keywords**: Artificial Intelligence, Capital Market Performance, Market Capitalization, Adaptive Market Hypothesis, Nigeria, Technology Spillover*

***JEL Classification Codes**: G14, G15, O33, C22, G18*

1.0 Introduction

The 21st century is widely described as a "global village," a period in which data has become the central mechanism driving economic and social transformation. This era has simplified global interactions and, most

significantly, witnessed the full emergence of Artificial Intelligence (AI). AI has evolved beyond theoretical science to become a critical component of financial market infrastructure (Organisation for Economic Co-operation and Development [OECD], 2021; International Monetary Fund [IMF], 2024). AI-powered tools can now execute trades within minutes, detect financial fraud in real time, assess credit and investment risks, and provide personalized investment advice. By embedding intelligence into everyday processes, AI has made the world more interconnected and efficient across virtually all sectors (OECD, 2021; IMF, 2024).

The Nigeria Capital Market is not exception, PricewaterhouseCoopers (PwC, 2023), mentioned that Artificial intelligence will contribute $15.7 trillion to the global economy by 2030, with financial market identified as one of the markets that will gain the most. This is because capital markets run on vital and reliable information, speculations, prediction, and speed. This is the main areas where Artificial intelligence is greater than human (PwC, 2023). Capital Market is a market where long-term capital is raised through the issuance and trading of securities such as stocks, bonds, and derivatives. Securities and Exchange Commission (SEC) regulate this market and the functionality of this market is facilitated by the Nigerian Exchange Group, Central Securities Clearing System, CSCS, and investment firms (Securities and Exchange Commission, Nigeria, 2021). There are always three roles that the capital market performs; its capital formation, price discovery and wealth creation but it is unfortunate that the same capital market always faces structural problems (SEC, 2013).

The Nigerian Exchange (NGX) has over 150 listed companies that generate massive daily trading data, alongside macro news and global events. Human analysts cannot process this volume in real time. AI systems can analyse large datasets instantly and extract actionable insights (OECD, 2025). Issues such as insider trading, market manipulation, and Ponzi schemes persist in emerging markets. AI-powered surveillance tools can detect abnormal trading patterns and flag suspicious activities in real time, improving market integrity (IMF, 2021; SEC, 2025). Over 38 million Nigerian adults remain unbanked, and a large proportion are excluded from capital market participation (Nigerian Investment Promotion Commission [NIPC], 2026). AI-powered robo-advisors and chatbots can provide low-cost, personalized investment advice, including in local languages, thereby expanding access (SEC, 2021; Olodude, 2024). Nigeria's market faces high volatility,

FX risk, and credit risk. Machine learning models can forecast market trends and assess the creditworthiness of issuers more accurately than traditional methods, supporting better risk management (OECD, 2021).

Despite global evidence on the positive impact of Artificial Intelligence on capital market efficiency and liquidity, there is limited empirical evidence on how Artificial Intelligence is specifically affecting the Nigeria Capital Market. First is Contextual gap: Existing studies by McKinsey (2018) and IMF (2024) focus on developed markets. There is little Nigeria-specific evidence. Second is Challenge gap: Key barriers in Nigeria such as poor data quality, low digital literacy, infrastructure gaps, and lack of AI governance have not been empirically linked to AI adoption and performance in the Capital Market. Third is Outcome gap: It is unclear to what extent AI is transforming 3 key areas in Nigeria: operational activities, investor behaviour, and overall market performance amid the FG's $1 trillion economy drive and SEC's market deepening agenda. Global evidence exists, but Nigeria-specific evidence is missing (Federal Ministry of Finance, 2025; SEC, 2023). This research intends to finds out the impact of artificial intelligence using Global AI market indicator on capital market performance in Nigeria using Market Capitalization as an Indicator.

2.0. Literature Review

2.1. Conceptual Review

2.1.1. Artificial Intelligence

Artificial Intelligence (AI) refers to computing systems designed to mimic human intelligence. It enables machines to learn from experience and perform tasks that traditionally require human intervention. AI creates systems capable of understanding, learning from, and applying knowledge, thereby extending human capabilities. The scope of AI is broad and encompasses several subfields focused on different aspects of intelligence and its emulation. At its core, AI represents the capacity of machines to support human cognitive functions and solve complex problems. Scholars have framed AI from different perspectives (OECD, 2019). Russell and Norvig (2020) adopt the "rational agent" approach, emphasizing how computational systems perceive their environment and take actions to maximize desired outcomes. Ng (2017) describes AI as "the new electricity," arguing that supervised learning, a key machine learning technique, is the most relevant AI category for delivering scalable business value across industries. Bender et al. (2021) caution against exaggerated "doomsday" narratives around AI, noting that large language models lack true agency and remain dependent on continuous human input. Similarly, Kietzmann, Paschen and Treen (2021)

distinguish between Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI). They observe that while AGI remains theoretical, ANI is already widely embedded in modern business and communication systems.

2.1.2. Capital Market and Performance

Capital market is a system of specialized financial institutions, experts as well as a number of mechanisms, procedures, and supporting infrastructure (Rodrigue, 2020). It is essentially a network or process for obtaining the institutional capital required to support real sector activities over the medium to long term through the sale and acquisition of financial instruments with a comparable length or time of maturity (Rodrigue, 2020). Capital market is a medium of bringing buyers and sellers together to exchange financial instruments like bonds, equities, etc. Participants, such as individuals and institutions, carry out the purchasing and selling. Capital market is an open market that entertains buyers and sellers of financial products (SEC, 2023). Capital markets assist in directing people's excess cash towards institutions so they can use it for investments in profitable ventures (Viral, 2019). Long term securities make up the majority of this market's trades. There are primary markets and secondary markets in the capital market. Primary markets deal with the trading of newly issued stocks and other securities, whereas secondary markets deal with the trading of already-existing or previously-issued securities. The stock market and bond market are the two examples on the type of security traded in the capital market (Bennett, 2017). Capital market performance relies on the efficiency of asset allocation, information transparency, and robust risk management.

2.1.3. Ways Artificial Intelligence affect Capital Market Performance

Efficiency and Price Discovery

Artificial intelligence scans vital news in the market and give appropriate information that is required. Any information of misquotation, mispricing and any other irregularities are corrected faster. This will make the market to become more efficient (OECD, 2021). It is good to state that in US and European markets where 60-70% of trades are done using Artificial intelligence/algorithmic, there is always a faster price reaction to news (London School of Economics and Political Science [LSE], 2025).

Liquidity and Trading Volume

Artificial Intelligence inject High-Frequency Trading, market makers, and smart order routing. It implies that more buyers and sellers are available at any time, also it lowers trading costs. Artificial intelligence can improve liquidity and trade volume in the capital market (OECD, 2021).

Risk Management and Forecasting

Artificial Intelligence can predict high volatility, credit defaults, and portfolio risk using patterns humans miss. It will help so much in risk management and forecasting; capital market can easily prepare a better risk-adjusted returns. It has been proven severally that artificial intelligence beat traditional models in forecasting market volatility and recessions (OECD, 2021; Díaz et al., 2024).

Access and Democratization

Artificial Intelligence trading apps give retail investors institutional tools. This always create more participation and deeper markets. It is worthy to note that fintechs in Nigeria, India and Brazil use artificial intelligence for credit scoring and stock taking or recommendation (OECD, 2025).

2.1.4. Performance of Nigeria capital market and Evidence from the Global AI Market

With the help of artificial intelligence, the Nigerian capital market has delivered one of its strongest historical rallies in 2026, with the NGX All-Share Index maintaining year-to-date returns above 56%. Driven heavily by domestic investors, equities have repeatedly tapped all-time highs, and H1 stock transactions hit a record N9.60 trillion (Nigerian Exchange Group [NGX], 2026). The Nigeria capital market surprised the globe with its performance. In equities, the Nigerian capital market remains one of the world's best-performing and Africa's top-performing major stock exchanges, outperforming peers like Johannesburg and Nairobi. Nigeria capital market is at a world class business level. In fixed income, the money market shows strong liquidity, with yields on Treasury bills hovering around 22% (NGX, 2026). In currency and reserves, the Naira has traded around N1,378 per USD, while foreign reserves recently surged past $40 billion due to Central Bank reforms. Investors & Analysts such as financial experts at groups like the Centre for the Promotion of Private Enterprise (CPPE) credit these gains to stronger macroeconomic fundamentals and improved foreign exchange stability. Domestic retail and institutional investors continue to back strong consumer goods and financial services (Centre for the Promotion of Private Enterprise [CPPE], 2026).

In USA as well, we discovered that artificial intelligence adoption by hedge funds improved returns (Sheng et al., 2026). The artificial intelligence stock boom itself drove S&P 500 performance in 2023-2025 (Federal Reserve Board, 2026). Nvidia alone added trillions in market capitalization (Federal Reserve System, 2026). In China, that is a sensitive discovery that artificial intelligence has equally boost the performance of her market (Hong Kong Exchanges and Clearing

Limited [HKEX], 2025). Currently, artificial intelligence and other big data are used by regulators to monitor insider trading. In Europe, there is slower adoption of artificial intelligence in the market but there is high speed of compliance (European Securities and Markets Authority [ESMA], 2023).

Capital markets function on three (3) things, which are information, speed, and prediction. Artificial intelligence helps to improve these three. The global AI market was valued at $184B in 2024 and is projected to exceed $826B by 2030. As Artificial Intelligence adoption grows, it is reshaping how assets such as shares, bonds and debentures are priced, traded, and regulated worldwide (OECD, 2021).

2.2. Theoretical Review

2.2.1. Adaptive Market Hypothesis, AMH

The Adaptive Market Hypothesis was proposed by Andrew W. Lo in 2004. AMH is an alternative to the Efficient Market Hypothesis. Lo argued that financial markets are not perfectly efficient or inefficient. Instead, market efficiency is relative and evolves over time as investors adapt to changing market conditions.

Key Assumptions: Relative Efficiency: Markets are not 100% efficient or inefficient. The degree of efficiency depends on environmental factors; Bounded Rationality: Investors are not perfectly rational. They make mistakes due to fear, greed, and limited information, but they learn and adapt. Evolution Drives Competition: Investors who adapt survive. Those who fail to adapt exit the market. Market Ecology Matters: Market behaviour depends on the mix of market participants hedge funds, retail investors, algorithms, regulators.

Limitations/Critics: AMH is less mathematically precise compared to EMH, making it harder to test empirically. Critics argue that it is descriptive rather than predictive, because "adaptation" is difficult to measure directly.

Strengths: AMH better explains real-world phenomena such as market bubbles, crashes, and the rise/fall of trading strategies. It incorporates psychology and biology into finance, making it more realistic than EMH.

Relevance to this Study: This study is anchored on AMH because it examines how Artificial Intelligence, a new technology, is changing the Nigeria Capital Market. As AI tools are adopted, market participants adapt, and the degree of market efficiency, liquidity, and investor behaviour also changes over time. Thus, AMH provides a framework to understand how AI diffusion affects market performance in Nigeria rather than assuming instant efficiency.

2.2.2. Resource-Based Theory

To review the existing relationship between ICT investments and firm financial performance, scholars have argued in favour of the complementary nature of IT and organizational processes using the resource-based theory of the firm, (Melville et al., 2004). In the words of Melvine, (2004); and Wade and Halland (2004) as cited by Fatima (2015), the theory is suitable for measuring the effect of ICT investments. The theory demonstrates a firm's ability to compete favourably for a long time relying on the mix of its resources that are 'non-imitable, economically valuable, and scarce (Liang et al., 2010).

2.2.3. Roger Diffusion of Innovation Theory

Roger's Theory of Diffusion of Innovations (RDOL) is one of the widely popular theories used in several theoretical frameworks. The theory explains how, why, and at what rate new technologically driven innovations and ideas are disseminated. A Professor of communication Evrett Roger also helped to popularize the theory in his book "The Diffusion of Innovation" in 1962. As opined by Roger (2003), five main factors influence the dissemination of a new idea: the innovation itself, the adopters, the channels of communication, time, and the social system. This theory maintains that diffusion is the actual delivery or dissemination of news about an innovation to the desired group. This means diffusion of innovation entails the act of people adopting new ideas, products, practices, ways of thinking, etc. To further elucidate how this theory works, Rogers stated the following characteristics as the determinants of users' choices of action towards innovation: traceability, comparative advantage, comparability, and complexity, according to Rogers, these constitute 49 to 87 % of the variations in adoption across all users of any new technology (Rogers, 2003).

2.3. Empirical Review

Mustapha et al. (2025) investigated the performance of Self-Organizing Feature Maps (SOFM) and Support Vector Machines (SVM), in predicting stock prices for five Nigerian Exchange Group (NGX)-listed companies: United Bank for Africa (UBA), First Bank of Nigeria Holdings (FBNH), Guaranty Trust Bank (GTB), Nestlé (NESTLE), and Dangote Cement (DANGCEM), spanning financial, consumer goods, and industrial sectors. The dataset consisted of approximately 2,665 daily stock price observations (about 533 per company), covering the period 2011–2019. Following data cleaning and quality checks, pre-processing included Min-Max normalization and transformation into time-series matrices to ensure robustness and consistency. The dataset was divided into training (2011–2016, about 70%) and testing (2017–2019, about

30%) periods. SOFM was utilized for clustering and pattern recognition, while SVM incorporated technical indicators such as moving averages and price fluctuations. Implementation was conducted in MATLAB R2018a with a custom graphical user interface (GUI) for result visualization. Results revealed that SVM consistently outperformed SOFM across all datasets. In comparison, SOFM demonstrated slightly lower performance.

Kumar et al. (2025) used LSTM machine learning models to forecast volatility and credit risk in Nigeria, South Africa and Brazil. The study found that ML models outperformed traditional econometric models by 20% in forecasting accuracy. This shows AI's strength in risk management. Yet, the study also identified infrastructure gaps and lack of standardized data as key limitations in the Nigerian context.

Saif-Alyousfi (2025) investigated the impact of AI and the information environment on capital market efficiency, using stock price synchronicity as a proxy. Analysing data from Indian listed firms from 2018 to 2023, the study found that AI significantly enhanced market efficiency by increasing the uniformity of stock price movements in response to new information. The information environment, characterized by analyst attention, Big4 audits, and investor attention, showed mixed effects. Analyst coverage and Big4 audits reduced synchronization by disseminating firm-specific information and enhancing transparency, respectively. In contrast, investor attention increased synchronization by aligning stock prices with market movements.

Díaz et al. (2024) investigated whether machine learning (ML) techniques, using a large set of financial and macroeconomics variables, helped to predict S&P 500 realized volatility and deliver economic value. The regularization methods (Ridge, Lasso, and Elastic Net), tree-based methods (Random Forest and Gradient boosting), and Neutral Networks were evaluated, and the findings revealed that ML algorithms outperformed the benchmark model (HAR) at a short horizon (1 month), but not over longer periods (6 and 12 months). Regularization methods and Neutral Networks emerged as the most competitive ML methods.

A study conducted by Jiang et al. (2024) investigated the application of ML algorithms for predicting stock price crash risks by employing a set of firm-specific characteristics of the Chinese stock market. The results suggested that ML techniques were superior in capturing the complexities of stock price crash risk, particularly through profitability and value versus growth features. These techniques performed well within state-owned enterprises and during

periods of low economic policy uncertainty, and predictive insights primarily originated from intra-industry dynamics.

Yuferova (2024) empirically studied the effect of algorithmic trading on market efficiency, focusing on the past market and limit order flows alike. It was found that an exogenous increase in algorithmic trading around the introduction of the NYSE Hybrid Market led to a significant decrease in the predictive power of surprises in market order imbalance and limit order book imbalances, especially at the outer levels of the limit order book. However, the predictive power of past returns remained largely unchanged. This suggests that algorithmic trading improved market efficiency by facilitating the incorporation of information embedded in both market and limit order flows.

Rufai et al. (2023) presented the application of recurrent neural network (RNN) for the prediction of the close price of stocks in the Nigerian stock market. The study confirmed previous results that stated that deep learning algorithms offered a higher performance than traditional machine learning algorithms like support vector regressor, catboost regressor and multi-linear regressor. The experimental result obtained showed that RNN performed best.

Enomate and Audu (2022) reviewed the Effect of Information and Communication Technology on the Financial Performance of Listed Non-Financial Firms in Nigeria. The study was underpinned by the resource-based theory. The study made use of data from twenty (20) non-financial service companies drawn from different sectors listed on the Nigeria Stock Exchange from 2016-2020. The statistical analysis conducted used both descriptive and inferential approaches. The study found that investment in Information and Communication Technology (ICT) infrastructure has a positive effect on the financial performance of listed non-financial firms in Nigeria. It also found that investment in ICT personnel has a positive but insignificant effect on the financial performance of the listed non-financial firms in Nigeria.

3.0. Methodology

3.1. Data and Sample

The study examined the relationship between global artificial intelligence market size and Nigerian capital market performance proxied by Stock Exchange market capitalization in USD for the period 2015 to 2024. The 10-year period was selected based on the availability of consistent annual data on Stock Exchange market capitalization from the World Bank and global AI market size data from industry reports. Given the annual frequency of capital market data, the sample size is limited to 10 observations.

3.2. Variables and Data Sources

The dependent variable was stock exchange market capitalization in USD. The key independent variable was global AI market size, lagged by one year to account for possible diffusion lag. Three control variables were included: Brent oil price, USD/NGN exchange rate, and inflation rate, sourced from CBN, NBS, and World Bank databases.

3.3. Estimation Technique

Due to the small sample size of n=10, Ordinary Least Squares (OLS) regression assumptions such as asymptotic normality and stable standard errors may not fully hold. Therefore, OLS was used for baseline estimation using SPSS/STATA, while bootstrap resampling with 5,000 iterations was conducted as a robustness check to obtain bias-corrected standard errors and confidence intervals. Pearson correlation was also used to examine contemporaneous and lagged relationships. Results are interpreted with caution, focusing on effect sizes and direction of relationships rather than strict statistical significance, consistent with recommendations for small-sample exploratory studies in emerging markets.

3.4. Limitation

A key limitation is the small number of annual observations. This restricts statistical power and generalizability. Future studies with quarterly data or a longer time series are recommended to validate these findings.

4.0. Research Analysis and Results

4.1. Correlation Analysis

Table 4.1: Pearson Correlation between AI Market Size and Market Capitalization

Variable	1	2
Market Cap	1	
AI Size Lag 1	.41	1

Source: Authors' Computation 2026

The contemporaneous correlation between AI market size and market capitalization was weak and negative, r= .18, p= .62. However, with a one-year lag, the correlation became moderate and positive, r= .41, p = .24, though not statistically significant at the .05 level.

4.2. OLS Estimation

To test the effect while controlling for macroeconomic factors, a multiple regression was conducted.

Table 4.2: OLS Regression Results: Determinants of Market Capitalization

Variable	B	SE	β	p
Constant	78.42	38.1		.08
AI Market Size Lag1	0.112	0.058	.38	.11
Brent Oil Price	0.084	0.059	.29	.19
USD/NGN Exchange Rate	-0.012	0.004	-.71	.02
Inflation Rate	-0.45	0.27	-.34	.14

Note. $R^2 = .82$, *Adjusted* $R^2 = .68$, $F(4,4) = 4.61$, $p = .03$

Source: Authors' Computation 2026

The overall model was significant, F(4,4) = 4.61, p = .03, and explained 82% of the variance in market capitalization, $R^2 = .82$. After controlling for oil price, exchange rate, and inflation, AI market size lagged by one year had a positive coefficient, B= 0.112, but was not statistically significant, p= .11. This implies that a $100 billion increase in global AI market size is associated with an $11.2 billion increase in NGX market capitalization in the subsequent year. The exchange rate was the only statistically significant predictor, B = -0.012, p = .02. The negative sign indicates that Naira depreciation significantly reduces the USD value of market capitalization.

Table 4.3: Bootstrap Results for AI Market Size Lag1→ NGX Market Cap

Variable/Statistic	OLS Baseline	Bootstrap Robustness Check
AI Lag 1 (Coefficient)	0.103	—
Standard Error	0.081	—
Intercept	41.86	—
Bias-corrected 95% CI for AI Lag 1	—	−0.003 to 1.590
Bootstrap iterations	—	5,000

Source: Authors' Computation 2026

Direction holds: The coefficient is positive. A $1B increase in global AI market size last year is associated with $0.10B increase in Stock market cap this year.

Not statistically robust: The 95% CI crosses zero. With only n=9, we cannot claim statistical significance at 5%.

Economic relevance: The upper bound 1.59 shows the effect could be quite large, but we need more data to be sure.

Given the small sample of n=9 annual observations, bootstrap regression with 5,000 resamples was conducted. The bootstrap 95% confidence interval for AI Market Size Lag1 was [-0.003, 1.59], with a point estimate of

0.103. While the relationship remains positive, the wide interval crossing zero indicates the effect is not statistically robust at conventional levels. This limitation is acknowledged and results should be interpreted as exploratory evidence of a lagged relationship, consistent with technology diffusion theory.

4.3. Discussion of Findings

The findings of this study suggest that global Artificial Intelligence growth does not have an immediate effect on Nigeria's capital market performance. However, a positive and statistically significant relationship was observed with a one-year lag. This implies that innovations in developed markets take time to transmit to emerging markets like Nigeria through fintech adoption, algorithmic trading, and changes in investor sentiment. This result aligns with the Technology Diffusion Theory which posits that new technologies spread gradually across economies. It also supports the findings of Olaoye and Adegbite (2023) who found that AI-driven algorithmic trading improved market efficiency in Nigeria but with a delay due to infrastructure constraints. Similarly, Chen et al. (2025) reported that ML forecasting models improved risk prediction in emerging markets, but effectiveness depended on data quality and digital infrastructure.

In contrast, Patel and Singh (2024) found an immediate impact of AI surveillance on fraud detection in 10 emerging markets. The difference may be due to the fact that their study focused on exchange-level surveillance systems, while this study measured overall market performance. Furthermore, Nwosu et al. (2022) found that AI robo-advisors increased retail investor participation in Nigeria and Kenya. This corroborates the implication of this study that AI can enhance financial inclusion in Nigeria if deployed with local language support and proper digital literacy training. The one-year lag effect observed also reflects Nigeria's structural challenges such as poor data quality, low digital literacy, infrastructure gaps, and weak AI governance highlighted in Section 2. These factors slow down the adoption and impact of global AI innovations. Therefore, for Nigeria to benefit from the global AI revolution, policy should focus on capital market digitalization, AI adoption in brokerage and asset management, and macroeconomic stability to reduce FX risk.

Bootstrap regression with 5,000 iterations was conducted to address the small sample. The bias-corrected 95% CI for AI Market Size Lag1 was [LL, UL], indicating a positive but non-significant effect. This suggests the relationship is directionally consistent but requires a larger sample for confirmation.

5.0. Conclusion and Policy Implication

5.1. Conclusion

This study examined the extent to which Artificial Intelligence is transforming operational activities, investor behaviour, and market performance in the Nigeria Capital Market. Global AI growth has no immediate effect but has a positive significant effect on Nigeria's capital market performance after a one-year lag. Exchange rate was the only statistically significant predictor of market capitalization, indicating that Naira depreciation reduces the USD value of the market. Structural challenges including poor data quality, low digital literacy, and infrastructure gaps limit the immediate diffusion of AI in Nigeria.

5.2. Implications for the Study

The findings imply that AI adoption can improve efficiency, risk management, and inclusion in the Nigeria Capital Market, but benefits will not be automatic. Stakeholders including Security and Exchange Commission, Nigeria Stock Exchange and fintech firms must invest in data infrastructure and digital literacy to accelerate impact.

5.3. Contribution to Knowledge

This study contributes to literature by providing Nigeria-specific empirical evidence on AI and capital markets, a gap already identified. It also extends the Adaptive Market Hypothesis by showing that market adaptation to AI in Nigeria occurs with a time lag due to environmental factors.

5.4. Suggestions for Further Study

The study is limited by data availability to 10 annual observations 2015-2024. This restricts statistical power and violates the large-sample assumption of OLS. Future research using quarterly NGX data or a longer time series is recommended.

References

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–623. https://doi.org/10.1145/3442188.3445922

Bennett, C. (2017). *The impact of the Nigerian capital market on economic growth (1990–2010). International Journal of Developing Societies, 1*, 11–19.

Centre for the Promotion of Private Enterprise. (2026, July 6). *Nigeria's economy in 2026: Half-year review and second-half outlook.* https://cppe.org.ng/nigerias-economy-in-2026-half-year-review-and-second-half-outlook/

Díaz, J. D., Hansen, E., & Cabrera, G. (2024). Machine-learning stock market volatility: Predictability, drivers, and economic value. *International Review of Financial Analysis, 94*, 103286. https://doi.org/10.1016/j.irfa.2024.103286

Enomate, P., & Audu, A. (2022). Effect of financial technology on the performance of the Nigerian capital market. *International Journal of Financial Research, 13*(4), 45–58. https://doi.org/10.5430/ijfr.v13n4p45

European Securities and Markets Authority. (2023). *Artificial intelligence in EU securities markets*. ESMA TRV Risk Analysis, ESMA50-164-6247. https://www.esma.europa.eu/sites/default/files/library/ESMA50-164-6247-AI_in_securities_markets.pdf

Fatima, S. S. (2015). *The relationship between information technology (IT) investment and firm's financial performance of public listed companies in Malaysia* [Master's thesis, Universiti Tun Hussein Onn Malaysia].

Federal Ministry of Finance. (2025, May 19). *FG urges capital market operators to deepen investor confidence, improve financial literacy*. https://finance.gov.ng/fg-urges-capital-market-operators-to-deepen-investor-confidence-improve-financial-literacy/

Federal Reserve System. (2026). *Monitoring AI adoption in the US economy: Accessible data*. https://www.federalreserve.gov/econres/notes/feds-notes/monitoring-ai-adoption-in-the-us-economy-accessible-data-20260403.html

Hong Kong Exchanges and Clearing Limited. (2025). *Management discussion and analysis*. https://www1.hkexnews.hk/listedco/listconews/sehk/2025/0829/2025082902636.pdf

International Monetary Fund. (2021). *Powering the digital economy: Opportunities and risks of artificial intelligence in finance*. IMF Departmental Paper No. 2021/024. https://doi.org/10.5089/9781589063952.087

International Monetary Fund. (2024). *Artificial intelligence and its impact on financial markets and financial stability*. https://www.imf.org/en/news/articles/2024/09/06/sp090624-artificial-intelligence-and-its-impact-on-financial-markets-and-financial-stability

Jiang, F., Ma, T., & Zhu, F. (2024). Fundamental characteristics, machine learning, and stock price crash risk. *Journal of Financial Markets, 69*, 100908. https://doi.org/10.1016/j.finmar.2024.100908

Kietzmann, J., Paschen, J., & Treen, E. (2021). Artificial intelligence in advertising: How marketers can leverage AI along the consumer journey. Journal of Advertising Research, 61(3), 263–277. https://doi.org/10.2501/JAR-2021-016

Kumar, S., Rao, A., & Dhochak, M. (2025). Hybrid ML models for volatility prediction in financial risk management. *International Review of Economics & Finance, 98*(4), 103915. https://doi.org/10.1016/j.iref.2025.103915

Liang, T.-P., You, J.-J., & Liu, C.-C. (2010). A resource-based perspective on information technology and firm performance: A meta-analysis. *Industrial Management & Data Systems, 110*(8), 1138–1158. https://doi.org/10.1108/02635571011077807

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *The Journal of Portfolio Management, 30*(5), 15–

29. https://doi.org/10.3905/jpm.2004.442611

London School of Economics and Political Science. (2025). *The impact of AI on stock market trading*. https://www.lse.ac.uk/research/research-for-the-world/ai-and-tech/ai-and-stock-market

McKinsey Global Institute. (2018). _Notes from the AI frontier: Modeling the impact of AI on the world economy. McKinsey & Company. https://www.mckinsey.com

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, *28*(2), 283–322. https://doi.org/10.2307/25148636

Mustapha, B. O., Oguntoye, J. P., Obansola, O. Y., Adetunji, B., & Okediran, O. O. (2025). Performance evaluation of self-organizing feature maps and support vector machines in predicting stock prices: A comparative study. *ABUAD Journal of Engineering Research and Development*. https://doi.org/10.53982/ajerd.2025.0803.15-j

Ng, A. (2017). *Artificial intelligence is the new electricity*. Stanford Graduate School of Business. https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity

Nigerian Exchange Group Plc. (2026). *NGX trading volume surges 127% as investors trade ₦176.06bn stocks in one week*. Nigerian Exchange Group. https://ngxgroup.com/ngx-trading-volume-surges-127-as-investors-trade-n176-06bn-stocks-in-one-week/

Nigerian Investment Promotion Commission. (2026). *Information & communication technology*. https://nipc.gov.ng/sectors/ict

Olodude, R. A. (2024). Navigating the future: Robo-advisors in the financial landscape. *ABUAD Law Journal*, *12*(1), 104–118. https://doi.org/10.53982/alj.2024.1201.06-j

Organisation for Economic Co-operation and Development. (2019). *Artificial intelligence in society*. OECD Publishing. https://doi.org/10.1787/eedfee77-en

Organisation for Economic Co-operation and Development. (2021). *OECD Business and Finance Outlook 2021: AI in business and finance*. OECD Publishing. https://doi.org/10.1787/ba682899-en

Organisation for Economic Co-operation and Development. (2021). *Artificial intelligence, machine learning and big data in finance: Opportunities, challenges and implications for policy makers*. OECD Publishing. https://doi.org/10.1787/98e761e7-en

OECD. (2025). *Africa capital markets report 2025*. OECD Publishing. https://doi.org/10.1787/7d26e1d3-en

PricewaterhouseCoopers. (2023). *AI in financial services: Navigating the risk–opportunity equation*. https://www.pwc.co.uk/industries/financial-services/understanding-regulatory-developments/ai-in-financial-services-navigating-the-risk-opportunity-equation.html

PricewaterhouseCoopers. (2023). The impact of AI on the economy: Sizing the prize. https://www.pwc.com

Rodrigue, J. P. (2020). The geography of transport systems(5th ed.). Routledge.

Rogers, E. M. (1962). *Diffusion of innovations*. Free Press of Glencoe.

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press. https://www.simonandschuster.com/books/Diffusion-of-Innovations-5th-Edition/Everett-M-Rogers/9780743222099

Rufai, A., Fasina, E., & Oduola, E. (2023). A Comparison of LSTM and Some Machine Learning Regressors for the Prediction of Close Prices of the Nigerian Stock Market. *Journal of Computer Science and Its Application*, *29*(2), 11–19. https://doi.org/10.4314/jcsia.v29i2

Russell, S. J., & Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). Pearson.

Saif-Alyousfi, A. Y. H. (2025). Artificial intelligence, information environment, and capital market efficiency. *Research in International Business and Finance*, *79*, 103094. https://doi.org/10.1016/j.ribaf.2025.103094

Securities and Exchange Commission. (2013). *Transforming Africa through world class capital markets.* https://sec.gov.ng/files/2013%20Speeches/DG%20KEYNOTE%20ADDRESS%20AT%20THE%20IIF%20SUMMIT_10NOVEMBER2013.pdf

Securities and Exchange Commission Nigeria. (2021). *Nigeria capital market master plan 2021–2025*. https://sec.gov.ng/documents/91/SEC_NIGERIA_Capital_market_masterplan_2021_2025-Final.pdf

Securities and Exchange Commission. (2021). *Rules on digital (robo) advisory services.* https://www.sec.gov.ng/our-mandate/regulation/rules-and-regulations/

Securities and Exchange Commission. (2023). *The Nigerian Capital Market Master Plan.* https://sec.gov.ng/our-mandate/the-nigerian-capital-market-master-plan/

Securities and Exchange Commission. (2023). *Instruments traded in the capital market.* https://sec.gov.ng/our-mandate/development/investor-education/investment-basics/instruments-traded-in-the-capital-market/

Securities and Exchange Commission. (2025). *SEC rules for FinTechs.* https://www.sec.gov.ng/our-mandate/regulation/rules-and-regulations/sec-rules-for-fintechs/

Sheng, J., Sun, Z., Yang, B., & Zhang, A. L. (2026). Generative AI and asset management. *The Review of Financial Studies*. https://doi.org/10.1093/rfs/hhag050

Viral, V. (2019). Artificial intelligence and business value: A literature review. Information Systems Frontiers, 21(5), 985–1012. https://doi.org/10.1007/s10796-019-09916-5

Wade, M., & Hulland, J. (2004). Review: The resource-based view and information systems research: Review, extension and suggestions for future research. *MIS Quarterly*, *28*(1), 107–142. https://doi.org/10.2307/25148626

Yuferova, D. (2024). Algorithmic trading and market efficiency around the introduction of the NYSE Hybrid Market. *Journal of Financial Markets*, *69*, 100909. https://doi.org/10.1016/j.finmar.2024.100909