JOURNAL OF INDIAN ECONOMY AND BUSINESS
Vol. 1, No. 1, 2024, pp. 43-66 • ISSN: 3048-5789

URL: http://www.pbjournals.com/jieb
Publisher of Open Access Journals

UNDERSTANDING HOW ARTIFICIAL INTELLIGENCE EXERT EFFECT ON THE STOCK MARKET IN BRICS NATIONS: A PANEL ARDL METHOD

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Article History
Received : 19 February 2024; Revised : 16 March 2024; Accepted : 27 March 2024; Published : 30 June 2024

Abstract: The present study examines the impact of artificial intelligence (AI) on the stock market (SM) along with other factors such as trade (tr), foreign investment (FDI), exchange rate (Ex), and inflation (In) from 2000 to 2022 in BRICS nations. BRICS countries were particularly selected due to the high potential for investment. The results show that AI, FDI, and trade have a positive effect on the stock market, whereas exchange rate and inflation have a negative effect. While in the short run, all factors except trade have a positive impact on stock market in BRICS nations. Furthermore, employing the Dumitrescu-Hurlin causality test, a bidirectional causal relationship was found between the stock market and FDI and the stock market and trade. A unidirectional causality was found between AI and the stock market. The findings suggested that policymakers should concentrate more on investment policies and integrating AI techniques for the growth of the stock market.

***Keywords*:** Artificial intelligence; FDI; Panel ARDL; Stock market; Trade

JEL Classification: C1, F10, G1.

To cite this paper:
Reshma Vattekkad, Pradeesh Kunchu, Mohandas V.K. & Dr. K. Manikandan (2024). Understanding How Artificial Intelligence Exert Effect on the Stock Market in Brics Nations: A Panel ARDL Method. *Journal of Indian Economy and Business*. 1(1), 43-66.

1. INTRODUCTION

During the last ten years, the stock markets of the BRICS nations namely Brazil, Russia, India, China, and South Africa—have experienced tremendous expansion. The growth rate of the BRICS member nations is expected to increase speedily in the near future, potentially surpassing the combined growth rates of the US and Europe by 2030 (Ganguly & Bhunia, 2022). Goldman Sachs initially created the BRIC taxonomy to describe Brazil, Russia, India, and China—a group of sizable rising economies with substantial room for expansion (Chatterjee & Naka, 2022). The first BRIC summit occurred in 2009, after the group was formally established in 2006. The organisation expanded for the first time in December 2010 when South Africa joined, becoming BRICS (Toloraya, 2018). With about 42% of the world's population, around 26% of the global GDP, 21% of exports, 16% of world imports (Larionova, 2020), and 19% of oil output, the BRICS group has grown to become one of the most significant economic blocs in the previous ten years (Panova, 2017). Beginning in early 2024, five additional countries—Egypt, Ethiopia, Iran, Saudi Arabia, and the United Arab Emirates (UAE)—joined this powerful alliance, which was renamed BRICS+ (Sayed & Charteris, 2024). High levels of political contact and establishing economic institutions like the New Development Bank have given the bloc a more institutional character, even though it is an informal arrangement without a charter (Airas, 2023). Given the growing political and economic ties among the bloc's members, there is some co-movement among the BRICS markets (Lehkonen & Heimonen, 2014).

The stock market gives buyers and sellers a common platform to trade equities (Voit, 2013). Individual investors can profit from the trading conveniences, while institutional investors can invest large sums (Enisan & Olufisayo, 2009). The stock market facilitates the economy's money movement. Additionally, it increases market liquidity and fosters an atmosphere conducive to IPOs and entrepreneurship. Levine and Zervos (1999) assert that the size of the stock market has a significant role in stabilising the methods of obtaining money to better support investments and the growth of the economy. It is essential to structural changes in any economy, from a conventional, inflexible, and unsafe bank-based economy to one that is more adaptable, secure, and impervious to shocks, volatility, and a lack of investor confidence (Stapley, 1986). Numerous studies examine the integration of global stock markets. Despite some indications that China is increasingly fragmented, Nayyar (2020) and Dsouza *et al*. (2024) demonstrate interconnectedness within the BRICS economies. For instance, Sharma *et al*. (2013) used the variance decomposition test and VAR model to identify interdependencies across the BRICS stock market based on daily data from April 1, 2005, to March 31, 2010. Using wavelet multiple correlation and daily data from January 4, 2005, to February 28, 2012, the researchers discovered that the chosen nine Asian countries were highly connected (Tiwari *et al*., 2013). Wu (2020) argues that association among the stock market across developing economies can be significantly skewed if the influence of global market forces is ignored.

At the same time, economic theory and empirical study have long been interested in and investigating the relationship among the macroeconomic variables and stock rate. Research has continuously acknowledged market indices and stock prices as valid indicators for evaluating economic conditions (Abbass *et al*., 2022). Stock market prices are strongly impacted by a nation's economic circumstances (Riaz *et al*., 2022). The stock market is also significantly impacted by macro factors, including GDP, interest rates, exchange rates (ER), and inflation (Gyamfi *et al*., 2021).

In every economy, foreign capital inflows (FCI) have been seen as the key to economic progress and expansion of the stock market (Adidren, 2023). Al-Delawi *et al*. (2023) use the ARDL approach to assess the short- and long-term effects of foreign direct investment (FDI) on stock market growth in Pakistan and the influence of exchange on stock market growth. In the short and long term point of view, the study shows that FDI has a substantively more significant and favourable effect on the stock market development. At the same time interest rates (IR) have been demonstrated to impact negatively, they are statistically negligible compared to exchange rates (ER), which also substantially impact stock market growth. Moussa and Delhoumi (2021) investigated the effects of exchange rates on the stock market of five MENA nations. Their findings supported the idea that returns on stock market asn exchange rate of the nations is cointegrated. Their findings also confirmed that, in contrast to Morocco, Turkey, and Jordan, the market index for Tunisia and Egypt is more susceptible to declines in exchange rates than to increases. Hence, it was identified that an increasing the value home currency is expected to boost returns in the Middle East/

North Africa (MENA) stock market. The Granger causality results of Jawaid and Ui Haq's (2012) study of the banking sector in Pakistan demonstrated a causal relationship between exchange rates and stock prices, in such a way that that changes in exchange rate (increasing) significantly boosts stock prices and vice verse. Khan (2019) looked at how the exchange rate affected the returns on the Shenzhen Stock Exchange and concluded that stock returns would suffer if the Chinese Yuan appreciated and vice versa. In the case of inflation, using monthly data, Kwofie *et al*. (2018) examined how inflation and currency rates affected Ghanaian stock market returns. The findings reveals that strong association between inflation and GSE market performance over the long run. A rise in present and anticipated inflation should raise predicted nominal dividend payments, according to Kellison's (1930) groundbreaking work, which argues that nominal stock returns act as a hedge against inflation. According to Alexakis *et al*. (1996), economies with low inflation rates, which are primarily found in developed capital markets, have stable stock prices, whereas economies with high inflation rates, which are primarily found in emerging capital markets, have volatile stock prices. Using the ARDL approach, Uwubanmwen (2015) investigated how the rate of inflation affected stock returns in the Nigerian stock market. The results indicated that returns of stock were negatively affected by the rate of inflation.

AI is one of the recent and most significant factors that is impacting the Research and use of AI technology in financial investing is growing. 90% of hedge fund trades are still carried out by a hardcoded process, even though the great bulk of these transactions are automated by computers (Kim and Chun, 1998). Therefore, there is still a lot of room for advancement in the ever-growing field of artificial intelligence. One of the key issues that artificial intelligence researchers are attempting to address is stock prediction. Because investors want to know when it's reasonable to acquire and sell a certain share. As a result, Y.F. Wang carried out a study on the subject called "Prediction of Stock Price Using Grey Prediction System." This work aims to use a mix of grey theory and fuzzification techniques to make an instantaneous stock prediction (Pagliaro, 2023). For example, a developed machine learning system called G-Score was proposed by Mohanram *et al*. (2005) to make stock trading decisions. They used financial reporting and basic research to assess three factors: accounting conservatism, naïve extrapolation, and predictability. Additionally, they demonstrated the algorithm's sufficiency by backtesting the trajectory of the US stock market from 1978 to 2001. Hence, AI has a crucial role to paly in the advancement and growth of the stock market.

Given the preceding circumstances, the major objective of this research is to investigate how the stock market (taking stock traded as a proxy) is affected by the technological factor, namely artificial intelligence (taking the patent application as the proxy), external factors (FDI, trade openness, and exchange rate), and internal factors (inflation), specifically in the context of BRICS nations. This study adds to the body of knowledge in several ways. First, there is a lack of research using the ARDL approach to investigate the long and short run impact of the aforementioned factors in BRICS nations for a period from the 2000s when the impact of technology became more visible in the stock exchange. Second, the study adds artificial intelligence as a factor affecting the stock market, which has been lacking in earlier research. Additionally, the research will offer some potential recommendations on the basis of the findings.

2. METHODOLOGY

2.1. Data

The current study analysed the dynamic short- and long-run effect of technology factors such as artificial intelligence (AI) along with open economy factors such as foreign direct investment (FDI), trade (Tr), and exchange rate (Ex); and internal factor, inflation (In) on the stock market (SM) (taking stock traded as a proxy) in BRICS nations by employing the panel autoregressive distributive lag model method. A time series dataset spanning over 23 years, from 2000 to 2022, was used in the investigation. Data on FDI, trade (Tr), exchange rate (Ex), inflation (In), and stock market (SM) (taking stock traded in current US dollars as the proxy) were sourced from World Development Indicators (WDI) (World Bank, 2024). Additionally, data regarding artificial intelligence were sourced from the OECD patent database. The stock market (SM) is the dependent variable in the current study. FDI, Tr, and stock traded were measured in terms of current US$ and inflation is calculated as consumer price (annual percentage), whereas the exchange rate is measured in terms of LCU per US$, period average. The OECD's patent databases, which offer comprehensive information on patent filings categorised by technological disciplines, including AI-related advancements like machine learning, robotics, and data analytics, are the source of the AI variable, which is defined as patents for technologies related to artificial intelligence. For all our data analysis and econometric modelling, we used EViews 12, an exhaustive econometric software. To ensure that the data was normally distributed, the factors were converted into logarithms. Table 1 provides a description of the variables used in the study, together with information on sources, rationale, and unit of measurement.

Table 1: Variable description

Type of variable		*Factors*	*Abbreviation*	*Units*	*Data source*
Output variable	Dependent factors	Stock traded	LnSM	Current US$	WDI*
Technology variable		Artificial Intelligence	LnAI	Patents for technologies related to artificial intelligence	WDI*
Internal factor		Inflation	LnIn	Consumer price annual %	WDI*
Open Economy Factors		Foreign Direct Investment	LnFDI	Foreign direct investment, net (BoP, current US$)	WDI*
		Trade	LnTr	Net trade in goods and services (BoP, current US$)	WDI*
		Exchange Rate	LnEx	LCU per US$, period average	WDI*

Note: *World development indicators

2.2. Specification of model

The panel ARDL approach were used for accomplishing the objectives, and similar models were used by studies such as Raihan *et al.* (2024), who focus on how AI affects the environment in G7 nations, and Joo and Shawl (2023), which focused mainly on the influence of FDI on economic growth along with trade, stock market capitalisation, and inflation as a few other important factors in BRICS nations. The present investigation employs the following model, which can be considered as an alternative version of the empirical model used by Raihan *et al*. (2024) and Joo and Shawl (2023), and this serves as the theoretical foundation. In this regard, we use the following equation.

$$SM_{it} = f(AI_{it}, FDI_{it}, Tr_{it}, Ex_{it}, In_{it}) \quad (1)$$

Where,

SM_{it} = Stock traded

AI_{it} = Artificial Intelligence

FDI_{it} = Foreign direct investment

Tr_{it} = Trade

Ex_{it} = Exchange rate

In_{it} = Inflation

't' represents 'time', 'i' represent 'observation' and 'f' represent 'function'.

From the equation (1), we derive the equation (2)

$$SM_{it} = AI_{it}^{\alpha1}. FDI_{it}^{\alpha2}. Tr_{it}^{\alpha3}. Ex_{it}^{\alpha4}. In_{it}^{\alpha5}. v_{t} \quad (2)$$

This study primary emphasis is on the following queries. Are BRICS nations stock markets affected by the aforementioned factors? What kind of effect does it have on the stock market? Previous research has shown contradictory results. For instance, in the research focusing on India, insignificant results are observed in the long-run effect of inflation and exchange rate changes on the stock market applying the ARDL model (Tejesh, 2024). Whereas Sreenu (2023) identified positive impact of exchange rate and inflation in the long term and a indirect impact in the short term on the stock market in India. In the study, Qamruzzaman and Wei (2018) identified a long-term correlation between the variables, such as financial development (application of technology) and stock market development. Nyasha *et al*. (2018) revealed that trade and exchange rates significantly and favourably affect the expansion of the stock market in Brazil. The fluctuation of the BRICS stock indexes, both past and currently, is significantly impacted by changes in exchange rates (Caporale *et al*., 2015; Mroua and Trabelsi, 2020). However, there is a lack of studies on studying the effect of artificial intelligence on the stock market in the BRICS nations using a high-end model like panel ARDL. By examining data from 2000 to

2022, this study attempts to fill these gaps and provide a thorough grasp of these factors determining the development of the stock market.

2.3. Unit root test

Unit root tests are often employed to test the stationarity of the factors employed in the analysis. As described in the research of Joo *et al.* (2023), If a data set's average, variance, and covariance remain constant, it is said to be stationary. In the current research, Im, Pesaran, and Shin (IPS), which has been introduced by Im *et al.* (2003), and LLC (Levin, Lin, and Chu) tests developed by Levin *et al.* (2002) are the first-generation unit root tests, and CIPS and CADF second-generation unit root tests, which take into consideration slope variation and cross-sectional dependency created by Pesaran (2007), were employed. Such similar tests were employed in the research undertaken by Raihan *et al.* (2024).

2.4. Panel cointegration

Assuming panel heterogeneity, the Pedroni panel cointegration test is used to determine if cointegration exists. Pedroni (1999) came up with two different evaluations. The first test employs a within-dimension technique and uses four statistical measures: panel v-statistics, panel rho-statistics, panel PP-statistics, and panel ADF-statistics. The second experiment employs a between-dimension method and three statistical measures: group statistics, group PP statistics, and group ADF statistics. If the p-value for any of these data points is less than the specified significance level, the null hypothesis—which holds that there is no cointegration—is rejected.

2.5. Panel ARDL

In the present research, the development of stock market is linked to technology factor such as artificial intelligence, (ii) open economy factor such as FDI, trade, exchange rate and (iii) internal factor such as inflation. The empirical model states that stock market development (taking stock traded as proxy) is a function of these technological, open economy factor as well as internal factor. In order to examine the association among the stock market and these explanatory factors, the study employs the following.

$$SM_t = \alpha_0 + \alpha_1 AI_t + \alpha_2 FDI_t + \alpha_3 Tr_t + \alpha_4 Ex_{t\,+}\ \alpha_5 In_{t\,+}\ u_t \tag{2}$$

Where α_0 is the intercept of the model, α_1 to α_5 are the coefficient that quantify the impact of explanatory factors in the dependent variable. Additionally, we convert our model to logarithmic form in order to prevent heteroskedasticity and autocorrelation (Erih *et al.*, 2014; Hassan and Muhammed, 2024).

Pesaran *et al.* (2001) developed the autoregressive distributed lag model, which is employed in this study, and it is more effective than any other cointegration technique (Panpoulou and Pittis, 2004). Both short- and long-run dynamics between the variables can be analyzed using the ARDL model when the independent variables in the model are I (0) and I (1) or jointly integrated (Fosu and Magnus, 2006). It is appropriate for time series data as it enables the inclusion of both stationary and non-stationary variables in this analysis (Fosu and Magnus, 2006). The current study employed panel ARDL. The primary justification for using panel data is that it assesses the impact collectively rather than individually, meaning that by adopting a panel perspective, relatively little information is lost (Baltagi, 2008). Furthermore, heteroscedasticity is not a problem in panel data analysis as panel data minimises the noise originating from the individual time series (Ahn *et al.*, 2013). Additionally, panel data is most appropriate in situations when data availability is a problem, especially in developing nations where short-term variables are accessible (Khelfaoui *et al.*, 2022). By accounting for subject-specific factors and dynamic changes brought on by repeated cross-sectional observations, panel estimate approaches account for this heterogeneity. Heterogeneous panel data modelling, or panel-ARDL, is the only focus of this work. This study on the stock market growth of the BRICS countries can employ the Panel Autoregressive Distributed Lag (ARDL) technique since it can evaluate both short-term and long-term dynamics between technology, open economy, and internal variables. In order to capture the distinct economic and technical landscapes of the BRICS nations, this approach must take into account variability across cross-sections. In contrast to conventional panel data techniques, Panel ARDL addresses the possibility of various temporal dynamics within each nation by permitting varying lag lengths for every variable (Rehman *et al.*, 2021). Furthermore, as is typical in financial and macroeconomic datasets, Panel ARDL excels at managing variables cointegrating at different orders (I(0) and I(1)). The dependent-independent variable relationship was determined via the following model.

$$\text{InSM}_t = \alpha_0 + \alpha_1\text{LnSM}_t + \alpha_2\text{LnAI}_t + \alpha_3\text{LnFDI}_t + \alpha_4\text{LnTr}_t + \alpha_5\text{LnEx}_t + \alpha_6\text{LnIn}_t + v_t \quad (3)$$

Equation (3) may be expressed as follows in ARDL form:

$$\Delta\text{LnSM}_t = \alpha_0 + \sum_{i=1}^{n1} \alpha_{1i}\,\text{LnSM}_{t-i} + \sum_{i=1}^{n2} \alpha_{2i}\,\Delta\text{LnAI}_{t-i} + \sum_{i=1}^{n3} \alpha_{3i}\,\Delta\text{LnFDI}_{t-i} + \sum_{i=1}^{n4} \alpha_{4i}\,\Delta\text{LnTr}_{t-i} + \sum_{i=1}^{n5} \alpha_{5i}\,\text{LnEx}_{t-i} + \sum_{i=1}^{n6} \alpha_{6i}\,\text{LnIn}_{t-i} + \beta_1\text{LnSM}_{t-1} + \beta_2\text{LnAI}_{t-1} + \beta_3\text{LnFDI}_{t-1} + \beta_4\text{LnTr}_{t-1} + \beta_5\text{LnEx}_{t-1} + \beta_6\text{LnIn}_{t-1} + e_t \quad (4)$$

When α_0 represents a drift component, Δ indicates the first difference between the variables, and e_t is the white noise error term. According to Gujarati and Damodar (2009), the term "white noise error term" refers to an uncorrelated random error term with zero mean and constant variance σ^2. In equation (4), the coefficients from 2nd to 7th (α_{1i} to α_{6i}) suggest an association in short-term and long-term relationships, as shown by the coefficients from 8th to 14th (β_1 to β_6). Utilizing the ARDL bounds testing technique, the long-term relationship between the variables is investigated. The F statistic is used in the bounds testing method to evaluate the hypothesis. This may be stated as follows.

H_0: There is no cointegration. ($\beta1= \beta2= \beta3= \beta4=\beta5=\beta6$)

H_1: Cointegration exists. ($\beta1\neq \beta2\neq \beta3\neq \beta4\neq \beta5 \neq \beta6$)

The null hypothesis is rejected if the calculated f statistic exceeds the upper limit value. If the calculated f statistic is smaller than the lower bound of the crucial value, the null hypothesis cannot be rejected. If the f statistic lies between the critical values of the lower and upper boundaries, we cannot make any inferences. The long-run elasticities, on the other hand, are the negative coefficients of a one-lag dependent variable, which permits the adoption of an unconstrained error correction model under the assumption established by Pesaran *et al.* (2001). The following is a representation of the ARDL model in its ECM form.

$$\Delta\text{LnSMe}_t = \alpha_0 + \sum_{i=1}^{n1} \alpha_{1i}\,\text{LnSM}_{t-i} + \sum_{i=1}^{n2} \alpha_{2i}\,\Delta\text{LnAI}_{t-i} + \sum_{i=1}^{n3} \alpha_{3i}\,\Delta\text{LnFDI}_{t-i} + \sum_{i=1}^{n4} \alpha_{4i}\,\Delta\text{LnTr}_{t-i} + \sum_{i=1}^{n5} \alpha_{5i}\text{LnEx}_{t-i} + \sum_{i=1}^{n6} \alpha_{6i}\text{LnIn}_{t-i} + \gamma\text{EC}_{t-1} + e_t \quad (5)$$

Where γ represents the adjustment speed and EC are the residual obtained from equation (5).

2.6. Robustness check

The robustness was evaluated in the paper using the DKSE, CCEMG, and AMG estimators. In addition to the residuals, Driscoll and Kraay (1998) employed the average values of the explanatory variable outcomes. Second, in the current study, we used the augmented mean group (AMG) estimator, which was proposed by Eberhardt and Teal (2010). Because the AMG estimator accounts for the CSD, mixed-order stationarity, and heterogeneity in the panel data, it produces more trustworthy results than first-generation estimators. The third estimator used in this work is the CCEMG approach, which was created by Pesaran (2006). Furthermore, both AMG and CCEMG perform better when estimating using common components that are uncertain and inconsistent. By taking into consideration temporal changes with varying factor pitches, the CCEMG resolves the identification problem.

2.7. D-H causality test

The causal association between the variables was determined in this study using the causality test created by Dumitrescu and Hurlin (2012). Because the cross-sectional dependency is taken into account, this test is superior than the panel Granger causality test.

3. RESULT AND DISCUSSION

3.1. Cross- Sectional Dependence Test

The results of the CDS test, which are shown in Table 2, indicate that the variables included in the current study have a substantial cross-sectional dependency. CD statistics are highly significant at the 1% level of significance, suggesting that the cross-sectional units are not independent of one another. This further implies that any changes or shocks to one of the panel's units

Table 2: Cross sectional dependence test

Variables	*CD- Statistics*	*P- Value*
LnSM	12.65***	0.023
LnAI	9.21***	0.001
LnFDI	7.54***	0.033
LnTr	16.48***	0.005
LnEx	9.34***	0.018
LnIn	14.96***	0.001

Source: Author's own evaluation using EViews will likewise affect the other units. Cross-sectional dependency is significant because it affects the results' validity and interpretation. Utilising second-generation panel data approaches that account for this reliance is essential to ensuring accurate and dependable findings.

3.2. Slope Homogeneity Test

The results of the Pesaran and Yamagata (2008) slope homogeneity test are shown in Table 3. The delta statistics are highly significant. Therefore, the slope homogeneity null hypothesis is rejected. In other words, the slopes in the panel data model are not uniform among the cross-sectional units. In other words, the influence of the exogenous variables on the endogenous factors (stock traded as a dependent variable in the current study) varies, leading to a slope heterogeneity issue.

Table 3: Slope Homogeneity test result

Test	*Δ statistic*	*P- value*
$\tilde{\Delta}$ test	**12.695**	**0.001**
$\tilde{\Delta}_{adj}$ test	**14.029**	**0.001**

Source: Author's own evaluation using EViews

3.3. Panel Unit root test

The findings of panel unit root tests, both the first generation (Levin, Lin, and Chu) as well as the second generation (CIPS and CADF), are shown in Table 4. Due to the higher level of p-value (more than 0.05), the factors such as stock traded (LnSM), trade (LnTr), and inflation (LnIn) at the level are non-stationarity, which falls short of the critical value needed to reject the null hypothesis of unit root at the level in both in both the first generation (Levin, Lin, and Chu) as well as the second generation (CIPS and CADF). When these variables are first differenced, the null hypothesis can be rejected. After differencing once, these factors are stationary. However, the factors such as LnFDI, LnAI, and LnEx indicate stationarity at level in both the generation test. Therefore, for further analysis, the variables LnSM, LnTr, and LnIn are converted to first differences.

3.4. Panel cointegration

The findings of Pedroni's cointegration test, which was used to determine whether there was a long-term link between the variables, are displayed in

Table 4: Panel Unit Root

Variables	*Levin- Chu*		*CIPS*		*CADF*		*Decision*
	I (0)	*I (1)*	*I (0)*	*I (1)*	*I (0)*	*I (1)*	
LnSM	-1.985 (0.0852)	-4.185*** (0.003)	-5.691 (0.619)	-10.418*** (0.0048)	0.6951 (0.417)	-6.112*** (0.0001)	I(1)
LnAI	-2.774*** (0.0048)	-3.148*** (0.0025)	-2.972*** (0.000)	-5.142*** (0.001)	-4.256*** (0.0067)	-8.522*** (0.002)	I(0)
LnFDI	-3.657*** (0.0039)	-7.698*** (0.0019)	-3.867*** (0.0004)	-5.029*** (0.0105)	-4.187*** (0.000)	-8.917*** (0.0023)	I(0)
LnTr	-1.265 (0.0896)	-3.617*** (0.033)	-3.611 (0.742)	-8.462*** (0.009)	-6.948 (0.258)	-10.697*** (0.0069)	I(1)
LnEx	-1.697*** (0.0347)	-3.694*** (0.012)	-1.745*** (0.023)	-3.981*** (0.0039)	-4.267*** (0.0477)	-7.239*** (0.0236)	I(0)
LnIn	-1.394 (0.336)	-3.911*** (0.003)	-4.333 (0.518)	-8.691*** (0.0006)	-2.364 (0.0755)	-6.311*** (0.0001)	I(1)

Source: Author's own evaluation using E-Views software

Table 5. Despite being statistically insignificant, the panel v-statistic and rho-statistic are both negative, suggesting conflicting evidence for a long-term relationship. Nonetheless, the highly significant panel PP-statistic and panel ADF-statistic results show that the no cointegration hypothesis is strongly refuted. Once more, the significantly negative Group PP and Group ADF statistics clearly contradict the null hypothesis that there is no cointegration between panels. The group rho-statistic is positive but not significant if individual autoregressive coefficients between dimensions are assumed. These findings typically demonstrate that there is evidence of cointegration across the variables in the panel dataset, despite possible variance in the autoregressive coefficients within and across dimensions.

3.5. Panel ARDL

Employing the panel ARDL technique, the study identified the short and long- run impacts of independent variables such as LnAI, LnFDI, LnTr, LnEx, and LnIn on the dependent variable LnSM. Table 6 presents the long-term findigs of the panel ARDL approach. According to the long-term coefficients of LnAI, it has a direct and significant association. A 1% rise in area would increase the stock traded (SM) by 0.46%. This finding was supported by Kim and Chun (1998), Mohanram *et al.* (2005), and Pagliaro (2023), who reported that AI has a positive role in the development of the

Table 5: Panel Cointegration result

Alternative hypothesis: common AR coefs. (within- dimension)				
	Statistic	*Prob.*	*Weighted Statistics*	*Prob.*
Panel v-statistic	-0.51258	0.75291	-0.71154	0.81248
Panel rho- statistic	-1.69471	0.93847	-1.69365	0.94171
Panel PP- Statistic	-7.26981	0.00001	-4.74128	0.00011
Panel ADF- Statistic	-3.19754	0.00014	-3.88894	0.00000
Alternative hypothesis: individual AR coefs. (between dimension)				
	Statistic		*Prob.*	
Group rho- statistic	-3.10055		0.4852	
Group PP- Statistic	-6.41173		0.0000	
Group ADF- Statistic	-7.0034		0.0002	

Source: Author's own evaluation using E-Views software

stock market. Because artificial intelligence (AI) improves data analysis, decision-making, and trading techniques, it increases market efficiency, which explains this positive and strong correlation. Increased use of AI by businesses or industries results in more knowledgeable investors and more efficient trading, both of which enhance stock market activity (SM). In a similar vein, FDI significantly and favourably affects LnSM; for every 1% increase in LnFDI, LnSM rises by 0.38 percent. This was supported by the results of previous studies conducted by Al-Delawi *et al.* (2023) and Adidren (2023). The fact that foreign direct investment (FDI) frequently contributes capital, knowledge, and market confidence to a nation's economy explains its favourable and noteworthy impact on stock market liquidity (LnSM). Increased FDI usually results in increased corporate expansion and investor confidence, which in turn boosts stock market trading activity (LnSM).

The long-term coefficients of trade (LnTr) reveal a positive and significant association. A 1 percent rise in LnTr increases the stock market (LnSM) by 0.31 percent. This was consistent with Dino's (2023) findings, which showed that a rise in trading volume had a beneficial impact on the stock prices of businesses that are part of the S&P 500 index. The positive and substantial correlation between trade (LnTr) and stock traded (LnSM) implies that the volume of stocks traded in the market is directly impacted by increasing trade activity. Increased economic growth, increased corporate profitability, and better market conditions are frequently the results of expanding trade. As a result, the stock market sees a rise in trading activity and investor confidence. A 1% rise in trade (LnTr) leads in a 0.31% rise in the stock traded (LnSM). This suggests that as trade increases, market participation and liquidity increase as well, increasing trading volumes overall. LnEx (exchange rate) has a negative but insignificant relationship with stock traded (LnSm) in the long run. Exchange rate variations may not have a major long-term influence on stock market activity, as seen by the negative but negligible association between exchange rate (LnEx) and stock traded (LnSM). Changes in exchange rates may have an impact on company profitability and international commerce, but other variables may outweigh their impact on stock trading volumes. The insignificance suggests that changes in exchange rates do not, in the long run, significantly influence changes in the quantities of stocks traded. However, studies that focus on the stock market and exchange rate generally produced contradictory findings, stating of negative and positive impact, with studies by Moussa and Delhoumi (2021) and Jawaid and Ui Haq (2012) showing positive and significant impact, whereas the negative impact has been identified in the research undertaken by Khan (2019).

LnIn (inflation) has a significant and negative effect on the stock market (LnSM) in the long run, indicating that a 1% rise in the inflation value will result in an approximately 0.09% decrease in stock traded. Rising inflation often reduces investor confidence and market liquidity, as seen by the negative and strong link between inflation (LnIn) and stock market activity (LnSM). Lower corporate profitability results from rising inflation since it reduces buying power, enhances uncertainty, and makes conducting business more expensive. As a result, stock trading may decline as investors get more cautious. The adverse effect of inflation on market participation and trading volumes is seen in the 0.09% decline in stocks traded for every 1% increase in inflation. These findings were in line with the study of Uwubanmwen (2015). This was in contradiction to the findings of Kwofie *et al.* (2018) and Alexakis *et al.* (1996).

Table 7 presents the short-term results of the ARDL technique. The rate at which any disequilibrium and long-term causality connections change from the short to the long term is indicated by the coefficient of the error correction term. According to the coefficient of the ECM, which is -3.156, the current year's correction for errors and shocks from the previous year will be made at a rate of 31.56%. The results of the short-term impact analysis

Table 6: Long term estimations of parameter in Panel ARDL method

Variables	*Coefficient*	*Std. error*	*t-statistic*	*Prob.*
LnAI	0.4612	0.1195	3.0111	0.038
LnFDI	0.3867	0.0798	1.4723	0.0007
LnTr	0.3124	0.1139	0.9273	0.00296
LnEx	-0.1872	0.1259	-0.1475	0.0712
LnIn	-0.092	0.9017	-1.0369	0.0051

Source: Author's own evaluation using E-Views software

Table 7: Short term estimations of parameter in ARDL method

Variables	*Coefficient*	*Std. error*	*t-statistics*	*Prob.*
COINTEQ01	-0.3156	0.0262	-4.1125	0.003
DlnAI	0.4856	0.1484	1.7451	0.0038
DLnAI(-1)	0.5369	0.1429	1.8513	0.0042
DLnFDI	0.3425	0.0236	-5.8613	0.0112
DLnTr	-0.1878	0.1497	4.0273	0.0011
DLnTr(-1)	-0.2196	0.8002	2.6003	0.0487
DLnEx	0.3636	0.1339	3.6696	0.003
DLnEx(-1)	0.4287	0.1691	3.1881	0.0047
DLnIn	0.1912	0.3205	2.9135	0.0311
DLnIn(-1)	0.2564	0.4112	2.1263	0.0035
C	-18.928	0.1013	-10.471	0.00

Source: Author's own evaluation using E-Views software

show that LnAI has the highest positive effects on the stock market (LnSM), with coefficient values of 0.53. Following artificial intelligence, LnFDI, LnEx, and LnIn also affect the stock market (LnSM) positively with coefficient values of 0.64, 0.42, and 0.25, respectively. However, in the short run, trade negatively affect the stock market with a 1% increase in trade (LnTr), which decreased the stock traded by 0.21. The possible immediate interruptions or adjustments that accompany an increase in trade are the reason for the short-term negative impact of trade (LnTr) on stock traded (LnSM). Higher trade volumes might cause market volatility in the near term as companies adapt to shifts in supply, demand, or outside variables like trade agreements or tariffs. Because of this uncertainty, stock trading activity may decline as investors get more cautious.

3.6. Robustness check

The findings of the long-run panel ARDL estimation were validated by employing DKSE, AMG, and CCEMG estimation. As displayed in Table 8, the findings are consistent with the panel ARDL estimation. The estimation of DKSE, AMG, and CCEMG confirmed that LnAI, LnFDI, and LnTr have a significant positive impact on LnSM in the long run. For instance, a one percent increase in LnAI increases LnSM by 0.53, 0.61, and 0.48 according to DKSE, AMG, and CCEMG, respectively. Additionally, as indicated by the panel ARDL findings, LnEx and LnIn have a negative impact, though LnEx has a negative impact; it is an insignificant impact on LnSM. Therefore, it can be concluded that the findings of DOLS, FMOLS, and CCR are consistent with the output of the panel ARDL model.

Table 8: DKSE, AMG and CCEMG estimation

Variables	*DKSE*	*AMG*	*CCEMG*
LnAI	0.53** (0.036)	0.61*** (0.001)	0.48**(0.036)
LnFDI	0.36** (0.025)	0.43*** (0.018)	0.46** (0.054)
LnTr	0.26** (0.031)	0.22*** (0.009)	0.18*** (0.005)
LnEx	-0.11** (0.041)	-0.09 (0.425)	-0.20 (0.521)
LnIn	-0.05** (0.030)	-0.12*** (0.013)	-0.14** (0.028)
Constant	5.698** (0.036)	14.864*** (0.007)	9.618*** (0.002)
Observations	115	115	115
Number of groups	5	5	5

Source: Authors' own evaluation using EViews.
Note: Standard error in parentheses; *** p< 0.01, **p<0.05

3.7. D-H Causality test

Table 9 presents the results of the Dumitrescu-Hurlin (D-H) causality test, which highlights the causal connection between the independent and dependent variables. The outcome reveals several important causal pathways. Because statistically significant results result in the rejection of the null hypothesis, the results of the Dumitrescu-Hurlin (D-H) causality test show that there is a unidirectional causal relationship between LnAI and LnSM. For instance, LnAI → LnSM suggests that artificial intelligence causes more stock to be traded. These findings were in line with the results of Chopra and Sharma (2021) and Dao *et al*. (2024). Furthermore, the bidirectional causation between LnSM and LnFDI and LnSM and LnTr. This suggests, for instance, stock-traded influence on FDI and vice versa. However, the study is unable to determine association among LnSM and LnEx and between LnSM and LnIn. This suggests that the stock market is not a reliable predictor of future exchange rate increases (Bhasin and Khandelwal, 2019).

This was contradictory to the findings of Abdalla and Murinda (1997). The relationship between exchange rates and stock prices in emerging nations' financial markets—India, Korea, Pakistan, and the Philippines—is examined by Abdalla and Murinde (1997), who come to the conclusion that, in all but the Philippines, there is a one-way causal relationship between exchange rates and stock prices. Thus, the results of the D-H causality test clarify the intricate relationships among technological factors, open economy factors, and internal factors with the stock market. These results highlight how crucial it is to implement coordinated policies that address FDI, trade, and investment in AI for achieving long-term growth of the stock market in BRICS nations.

Table 9: D-H Causality test

Null hypothesis	*W- Stat.*	*Zbar-Stat.*	*Prob.*	*Decision in N-Hypothesis*	*Causality direction*
LnSM ≠ LnAI	4.5971	2.9485	0.6358	Accept	LnSM ≠ LnAI
LnAI ≠ LnSM	2.3694	1.4259	0.0032	Reject	
LnSM ≠ LnFDI	1.5749	0.9647	0.0012	Reject	LnSM↔LnFDI
LnFDI ≠ LnSM	5.1571	3.8912	0.0033	Reject	
LnSM ≠ LnTr	6.2941	4.0028	0.0001	Reject	LnSM↔LnTr
LnTr ≠ LnSM	7.2642	6.1758	0.0051	Reject	
LnSM ≠ LnEx	5.1025	3.3695	0.6325	Accept	LnSM ≠ LnEx
LnEx ≠ LnSM	6.0785	5.0044	0.4821	Accept	
LnSM ≠ LnIn	9.3698	6.7852	0.5147	Accept	LnSM ≠ LnIn
LnIn ≠ LnSM	4.9517	2.1025	0.9654	Accept	

Source: Authors' own evaluation using EViews

4. CONCLUSION

In conclusion, the stock market development in BRICS nations, which spans 23 years, from 2000-2022, reveals noteworthy correlations with technology, open economy and internal factors. AI has the most long-term and short-term beneficial influence on the stock market in the BRICS countries when combined with sophisticated econometric techniques and the autoregressive distributed lag model (ARDL). In a similar vein, trade and FDI have long-term beneficial effects on the stock market. While exchange has little long-term negative impacts on the stock market, in has a negative and considerable long-term impact. In the near term, the stock market is positively impacted by FDI, exchange, and inflation, but trade has a large negative link. Likewise, there is a two-way causal relationship between commerce and the stock market with FDI. AI has a unidirectional association with the stock market. With an ECM coefficient of –3.156, the rate at which errors and shocks from the last years' will be adjusted in the present year is inferred to be 31.56%.

The study's conclusions indicate that in order to successfully support BRICS stock market, officials need to design and implement policies that eliminate barriers to market capitalisation and liquidity. The research suggests that officials loosen some of the requirements for companies have a listing on the stock exchange and thoroughly review the stock market regulations. The desire of more internal and external businesses to list will raise the stock market's liquidity. As the stock market responds to the information in the market in which they operate, managers must closely watch stock market trends and movements in order to spot possible hazards and opportunities, which is possible with the use of AI-related technology. By encouraging savings, diversifying with liquid assets, and granting access to emergency finance facilities to sustain operations in the event of irregular cash flows, management may help enterprises endure market shocks. Therefore, for lessening the effect of market volatility on their company operations and achieve continuous development, managers in an unstable economy should keep an eye on market trends, properly manage financial resources, hedge their portfolios against market risks, and modify their business strategy, which can be done by the application of artificial intelligence.

According to the study, stability in real interest rates necessitates stability in stock market activity, which in turn calls for the strongest possible control over inflation rates. The findings demonstrate a strong correlation between monetary policy and stock market investments (Eldomiaty *et al.* 2019). It also suggests that macroeconomic policies be implemented and a tax-free market environment be created in order to increase and draw FDI which could boost economic growth and stock market development. According to the study's policy implications, government representatives should enact sound macroeconomic laws and provide a tax-free marketplace to attract foreign direct investment and support the BRICS stock market and economics (Al-Delawi *et al.* (2023).

Declaration of Competing Interest: The authors do not have any conflict of interest.

Ethics approval and consent to participate: This research did not involve human participants, animal subjects, or any material that requires ethical approval.

Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

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