Asian Journal of Economic Modelling
ISSN(e): 2312-3656
ISSN(p): 2313-2884
DOI: 10.55493/5009.v13i4.5728
Vol. 13, No. 4, 639-651.

URL: www.aessweb.com

The impact of artificial intelligence on international trade in selected Sub-Saharan African countries

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Article History
Received: 8 August 2025
Revised: 10 October 2025
Accepted: 21 October 2025
Published: 19 November 2025

Keywords
Artificial intelligence
GMM
International trade
Panel data
Sub-Saharan Africa
Technology.

JEL Classification:
F13; F14; O30.

ABSTRACT

The primary objective of this paper was to empirically examine the impact of artificial intelligence on international trade in selected Sub-Saharan African countries for the period 2020 to 2024. The study utilized the Generalized Method of Moments (GMM) estimator to analyze annual panel data. The findings indicate that artificial intelligence has a positive and statistically significant effect on trade flows. This suggests that artificial intelligence influences international trade in Sub-Saharan African countries. Additionally, the results confirm that inflation and gross domestic product (GDP) significantly impact international trade. Overall, artificial intelligence, inflation, and GDP play crucial roles in shaping international trade in Sub-Saharan Africa. The outcomes of this research underscore the important contribution of artificial intelligence to international trade in the region. Consequently, this study advocates for the adoption and utilization of artificial intelligence technology to enhance trade activities. Furthermore, governments should consider revising policies and regulations within the trading sector to facilitate the adoption and utilization of artificial intelligence. Such measures may strengthen global trade governance and promote globalization. When formulating policies related to artificial intelligence, policymakers should also account for other factors affecting international trade, such as GDP and inflation.

Contribution/ Originality: Most previous research on this topic primarily focuses on systematic review and conceptual methods, neglecting empirical analysis. Only limited studies have considered empirical analysis; consequently, this study fills the gap by empirically investigating the influence of AI on international trade in selected Sub-Saharan Africa, thereby providing data-driven evidence.

1. INTRODUCTION

In recent years, Artificial Intelligence (AI) has witnessed remarkable advances and growth, reaching unprecedented levels. AI can be widely described as a machine-based method capable of making predictions, recommendations, or decisions that influence real or virtual settings, founded on a specific set of human-defined objectives (Achar, 2019; Organisation for Economic Co-operation and Development, 2019). AI is viewed as one of the key drivers of the technological, organizational, and societal revolution at the beginning of the 21st century. According to Wu (2023), AI technology symbolizes a milestone revolution in the internet and computer age. Its developing sophistication and prevalent use could considerably transform economic and social development, comparable to past transformative discoveries like steam engines and computers, driving new economic growth in the 21st century. Advancements in AI have led many countries to integrate trade with evolving technologies (Zhao & Zhou, 2021).

The usage of AI technology enhances trade efficiency by augmenting supply chains, streamlining compliance, creating new value from data, and reducing trade costs (Agrawal, Gans, & Goldfarb, 2017; Wu, 2023). This fosters smoother international trade and accelerates international trade growth. Moreover, AI is poised to significantly influence international trade, with numerous applications being developed in recent years. Cazzaniga et al., (2024) contends that AI offers noteworthy opportunities in the trade sector, ranging from augmenting productivity and refining decision-making to boosting predictive abilities and problem-solving skills. Despite the benefits that AI offers across numerous applications and industries, it also brings obstacles that include governance and responsible usage, with potential risks to society, consumers, and trade security (Achar, 2019). As nations navigate these complexities of AI, regulatory frameworks at both national and international levels may expand, significantly impacting international trade patterns. International trade can be described as a flow of goods and services between countries (Mcconnell, 2001). This flow of goods and services between countries connects the domestic economy with the global economy and thus functions as a channel for economic growth.

Africa has actively incorporated AI as technology gains traction worldwide. Significant progress has been made in various sectors of the African continent, with several institutions embracing and integrating AI in different forms into their daily operations (Murungu, 2024). AI has been incorporated into the financial sector, agricultural sector, public service, and other areas across the continent (Eke, Wakunuma, & Akintoye, 2023). For example, in Kenya, several AI applications are in place to improve agricultural trade by augmenting crop yields through the detection of pests and diseases in crops (Akello, 2022). Moreover, AI applications have advanced trade logistics in South Africa. In recent years, institutions in SA have leveraged AI technologies to improve port operations and optimize logistics (Murungu, 2024).

The AI technology presents the African continent with massive opportunities to transform its trading environment by improving accessibility to an inclusive market and promoting innovation and economic growth. Nevertheless, several obstacles and risks still deter the full application of AI technology on the African continent, including restricted connectivity, slow data processing capabilities, poor infrastructure, weak regulatory frameworks, and persistent data security concerns (Wakunuma & Eke, 2024). Moreover, the continent faces limited access to connectivity and relevant data, which are imperative for the effective implementation of AI technology. Data privacy and security remain significant obstacles, hindering the full implementation of AI in the trading sector (Okolo, 2023). International trade serves as a key driver of global economic growth, and the extensive adoption of artificial intelligence could significantly reshape its structure and operational dynamics. Given the opportunities and challenges presented by the application of AI in the trading sector, the authors are convinced that empirical research should be conducted around AI, specifically by investigating its impact on international trade.

Recent studies on the influence of AI on international trade have focused on developing and developed countries or countries outside the African continent. For instance, Wu (2023) focuses on the Organisation for Economic Co-operation and Development (OECD) countries, while Tay (2021) zooms on 196 countries, and Qian and Lai (2024) have focused on 139 countries. This study contributes to understanding the complexities of AI by empirically investigating its influence on international trade in selected Sub-Saharan Africa. To the best of the authors' knowledge, there are limited, if any, econometrics and empirical studies on the effect of AI on international trade, specifically for African countries. As a result, this study is among the first to empirically investigate the effect of AI on international trade in the African continent. The main goal of this study is to empirically assess the impact of Artificial Intelligence on international trade in Sub-Saharan Africa. In addition, this study seeks to respond to the following question: How does Artificial Intelligence affect international trade in Sub-Saharan Africa? As such, this study aims to help trade policymakers uncover the effect of AI on international trade. This field is understudied;

therefore, this study contributes to existing literature, and its findings could be used by policymakers and researchers to make informed decisions regarding the application of AI in the trading sectors.

This article is structured as follows: the subsequent section analyzes the current body of information on AI in the field of trade. The third section delineates the data and methodology used in this study. The fourth section presents the empirical findings, and the final section concludes and discusses the results of the study.

2. LITERATURE REVIEW

This section examines literature on the nexus between artificial intelligence and trade. It is divided into two subsections: the theoretical framework and empirical literature. The theoretical framework explores key theoretical concepts that provide valuable insights into the application of technology and innovation in trade, with particular emphasis on artificial intelligence. The empirical section reviews findings from existing studies on artificial intelligence and trade.

2.1. Theoretical Framework

Several theoretical frameworks offer valuable insights into the application of technology and innovation in trade, particularly in relation to Artificial Intelligence. For this study, only the Technology Acceptance Model (TAM) and Neo-technology theory of international trade are reviewed.

2.1.1. Technology Acceptance Model

According to Bannister (2023), the Technology Acceptance Model (TAM) was first introduced by Fred Davis in the 1980s and has since been used to evaluate the acceptance of new technologies such as Artificial Intelligence (AI). This TAM is one of the most widely adopted frameworks for understanding user acceptance and the adoption of innovative technology. The model includes perceptions of usefulness (PU) and ease of use (PEOU) as factors that influence the adoption of new technologies. However, to better explain Artificial Intelligence, Venkatesh and Davis (2000) extended the TAM by incorporating additional variables, social influence, and cognitive instrumental processes to enhance its predictive power. In this model, it was proposed that external factors, including social influences and cognitive instrumental processes, shape individuals' perceptions of usefulness (PU) and ease of use (PEOU), which, in turn, influence their intention to adopt technology and ultimately determine their actual usage of the system. For instance, social influence such as trust is a subjective mindset that encourages individuals to take risks in decision-making. Trust in technology empowers users to rely on a device to accomplish their intended objectives, such as utilising an AI-powered tool to forecast trading trends and make informed choices.

In addition, this model can be deployed to understand how new technologies are used, particularly in the trading sector. This model contends that entrepreneurs or businesses are more inclined to embrace new technology if they recognize it as valuable to their operations, easy to use, and beneficial for both them and their customers (Murungu, 2024). The adoption of TAM in this study is based on the recommendation that it can be applied where AI adoption is in its infancy. The African continent is still developing, and there are some countries where people do not yet have adequate internet access.

2.1.2. The Neo Technology Theory of International Trade

The Neo-technology theory of international trade is derived from the product cycle hypothesis pioneered by Vernon (1966). The theory claims that technological progress and product innovation are the major drivers of international trade. Moreover, this theory underlines internally driven technological innovation and differences in technology levels between industries and countries as key determinants of international trade (Patibandla, 1994). According to Borkakoti (1998), this theory is dynamic for two reasons: (i) technological innovation occurs in the development of economic growth, and (ii) the monopoly of new technologies is only short-term as other nations adopt and reproduce it after a lag time. The central claim is that international trade emerges from the continuous cycle of creating and distributing new technologies among nations. This theory offers a robust framework for understanding the influence of AI on international trade in Africa by emphasizing technology as a source of international trade.

2.2. Empirical Literature Review

This section provides a literature review of recent and pertinent studies on AI in relation to trade. A topical study by Qian and Lai (2024) investigated the effect of AI on international trade for 139 countries in 2021. The study used the Ordinary Least Squares technique to examine cross-sectional data. It found that in nations with a high Government AI Readiness Index, AI technology plays a crucial role in enhancing the expansion of international trade. Nevertheless, a strong negative correlation exists between the number of AI-related patent applications and the levels of imports and exports across countries. Wu (2023) explored the utilization and influence of AI technology on international trade in OECD countries. Using panel data analysis, the study found that in China and some OECD countries, AI has a significant positive effect on export and import trade. In this regard, the current study endorses the application of panel analysis to account for the drawbacks of time series.

Goldfarb and Trefler (2018) examined key elements of AI in relation to these dimensions and outlines the attributes of a suitable international trade model within the AI context. The study was conducted on the following countries: United States (U.S), United Kingdom (U.K), China, Singapore, Japan, Australia, Canada, India, Hong Kong, Germany, France, Israel and Italy. This study followed a conceptual and analytical method. The study ultimately outlines policy implications in relation to investments in research and internal policies including data localisation, privacy, competition and standards. The authors emphasise that a full insight into AI's influence on trade remains partial, with much still to be explored. Even though this study offers important insights into the relationship between international trade and AI, it lacks empirical evidence due to the conceptual method. The current study overcomes this limitation by providing empirical evidence of the relationship between international trade and AI.

Murungu (2024) explored the challenges and opportunities of generative AI and trade in Africa using a descriptive research design. The study underscores that generative AI is a significant factor of transformation and economic growth, boosting automation, innovation, and job creation. Furthermore, in the African economic landscape, the spread of AI increases democratized access and inclusion in the international market. Murungu (2024) further highlights that AI adoption faces challenges such as inadequate infrastructure, skills shortages, and weak regulations. The study concludes that key actions include strengthening regulations, implementing targeted training programs, and fostering public-private partnerships to drive investment and integration of generative AI. While the findings of this study are important, the method followed by Murungu (2024) has limitations in testing hypotheses and relationships. As a result, the current study examines the relationship between international trade and AI.

Achar (2019) explores early costs concerning the effect of AI on international trade, focusing on China using a thematic analysis. This study demonstrates that AI developments are essential in tradable areas such as ICT goods and services. Achar (2019) also emphasizes the importance of commerce in products, services, human expertise, and data for AI. Moreover, obstacles related to services, commodities, people, and data limit AI deployment. Nonetheless, this study does not provide empirical evidence; therefore, the current study addresses this weakness by providing empirical evidence of the relationship between international trade and AI.

Jayathilaka (2022) investigated the function of AI in advancing international trade. The study used random effect and fixed effect panel methods to analyze 150 countries between 2018 and 2021. The findings indicate that a nation's AI capabilities significantly and positively influence its trade. Moreover, the study concludes that there is a statistically significant positive association between gross domestic product and exchange rate with trade, while trade restrictions and inflation have an inverse and significant influence on trade. Jayathilaka (2022) suggests that enhancing national capacity stimulates trade volume. Furthermore, AI can drive economic growth and expand international trade opportunities by improving productivity. The current study endorses the application of panel analysis to account for the drawbacks of time series.

The key gap identified in the aforementioned studies is that the works of Achar (2019), Goldfarb and Trefler (2018), and Murungu (2024) are primarily discussions or systematic reviews. They lack empirical analysis, which this study addresses by undertaking an empirical investigation into the influence of AI on international trade in Sub-Saharan Africa.

Furthermore, while some studies have explored this field, they primarily focus on developing and developed countries or nations outside the African continent. For example, Wu (2023) examined OECD countries, Tay (2021) analyzed 196 countries, Jayathilaka (2022) focused on 150 developing and developed countries, and Qian and Lai (2024) studied 139 countries.

This study distinguishes itself by empirically assessing the effect of AI on international trade, specifically in Sub-Saharan Africa. Moreover, this investigation is among the first to undertake an empirical investigation into AI's influence on international trade within the African continent.

3. METHODOLOGY

The primary purpose of this section is to outline the methodology followed in this study. This analysis adheres to the empirical model proposed by Jayathilaka (2022), whose paper examined the role of AI in accelerating international trade for 150 developing and developed countries using panel data. The model employed by Jayathilaka (2022) is specified as follows:

$$Trade_{it} = a_i + a_1 AI_{it} + a_2 GDP_{it} + a_3 INF_{it} + a_4 TR_{it} + a_5 EX_{it} + u_{it} \quad (1)$$

Where *it* refers to the time period *t* in country *i*. Trade denotes the trade volume of the country; AI stands for Artificial Intelligence; GDP refers to Gross Domestic Product; INF represents inflation; TR signifies trade restrictions; and EX denotes the exchange rate. Moreover, and are parameters and the error term, respectively. The model given by Equation 1 suggests that this study models trade as a function of Artificial Intelligence, inflation, GDP, trade restrictions, and exchange rate. This study modifies the model given by Equation 1 by removing trade restrictions.

This variable is omitted due to unavailability of data. Although trade restriction is an important factor of international trade, its exclusion is a limitation as it may introduce bias in the estimated model. Nonetheless, the bias in the coefficients of the variables may be trivial; as a result, the computed coefficients are interpreted with caution. The modified model is given as follows:

$$Trade_{it} = a_i + a_1 AI_{it} + a_2 GDP_{it} + a_3 INF_{it} + a_4 EX_{it} + u_{it} \quad (2)$$

In this study, international trade is represented by trade percentage of GDP, which is calculated as the percentage of the sum of exports and imports relative to GDP. Thus, international trade is described as a percentage of the sum of exports and imports in relation to GDP. Additionally, Artificial Intelligence in this study is measured by a government AI readiness index, which reflects how prepared a country is to implement AI in the provision of public services.

Yearly panel data for the variables presented in the empirical model, as specified in Equation 2, were sourced from the International Monetary Fund, Oxford Insights Reports, World Bank, and African Development Bank database for the period spanning from 2020 to 2024. The selected study period was motivated by the availability of Government AI readiness index data and the development of national Artificial Intelligence approaches in Africa. Only 37 Sub-Saharan African countries were sampled in this study. The selection of these countries was based on the availability of data, particularly for Artificial Intelligence. Therefore, some countries were omitted due to the unavailability of data.

Table 1. Data description.

Data name	Description	Source
Trade	Trade (% of GDP)	African Development Bank
Artificial intelligence (AI)	Government AI readiness index	Oxford Insights Reports
Gross domestic product (GDP)	GDP growth (Annual %)	World bank
Inflation (INF)	Inflation, consumer prices (Annual %)	World Bank and African Development Bank
Exchange rate (EX)	Official exchange rate (LCU per US$, period average)	International Monetary Fund and African Development Bank

Table 1 presents data description and sources. To estimate the effects of Artificial Intelligence on international trade in Sub-Saharan Africa, the authors employ the Generalized Method of Moments (GMM) estimator, pioneered by Anderson and Hsiao (1982); Arellano and Bond (1991), as well as Arellano and Bover (1995). This estimator uses suitable lags of the instrumented indicators to create internal instruments while leveraging the pooled length of the panel dataset. Consequently, the method imposes no limitations on the dimension of each specific time length within the panel. This allows for the application of an appropriate lag element to handle the dynamic characteristics of the data. Moreover, this study employs panel data that has a short time span, i.e., a short time series with a relatively large cross-sectional dimension. Consequently, the GMM estimator is efficient when the sample has a large proportion of units compared to the time period (Farzana, Samsudin, & Hasan, 2024), which is the case with our sample. In addition, Roodman (2009) provides a rule of thumb for the selection of the GMM, i.e., the time period must be shorter than the number of cross sections being studied. Unlike the pooled mean group (PMG) estimator, which is efficient when the sample has a small proportion of units compared to the time period. The GMM estimator model is given by the following equation.

$$Y_{it} = \vartheta Y_{it-1} + \beta X_{it} + n_i + \varepsilon_{it}\ ; i = 1.2,3, \dots, N\ ; t = 2,3, \dots, T \qquad (3)$$

where ϑY_{it-1} is the lag value of trade; X_{it} is regressors comprising Artificial Intelligence, GDP, inflation, trade restrictions and exchange rate; n_i denotes an individual effect that is fixed over time and ε_{it} is an error term.

The dynamic specification in Equation 3 implies that the individual fixed effects are associated with the lagged regressand, and that certain regressors may be endogenous. This can lead to discrepancies and biased inferences in Ordinary Least Squares (OLS), fixed effects, and random effects estimators. Additionally, these estimators are violated in the presence of heteroskedasticity and normality issues. Nonetheless, the Generalized Method of Moments (GMM) is superior in addressing these issues. Moreover, Arellano and Bond (1991) highlight that GMM allows the use of lag variables as regressors to handle dynamic parameters and unobserved specific effects. Hence, the lagged regressand becomes part of the regressors linked with the model's random error terms to capture dynamic effects. In this study, a one-year lagged regressand is used to capture the dynamic effects and unobserved specific effects. Furthermore, conforming with traditional mechanisms of GMM function, the Arellano and Bond (1991) autocorrelation test [AR (2)] of the model must not be rejected for the lack of autocorrelation in the residuals. In a similar manner, the null hypothesis of the Hansen test should be accepted, as it indicates that the instruments are not correlated with the error term and are therefore valid.

Prior to estimating the GMM, pre-model estimation tests such as descriptive statistics, the matrix of pairwise correlation coefficients, panel unit root tests, panel co-integration tests, and residual diagnostic tests are conducted to ensure that the variables employed in this study comply with the requirements of the estimator.

4. RESULTS ANALYSIS AND INTERPRETATION

This section provides results analysis and interpretation, starting with descriptive statistics, progressing to pairwise correlation results, then to panel unit test results, cointegration test results, panel OLS diagnostic results, and the panel system GMM estimator results.

4.1. Descriptive Statistics

Table 2 provides the results of the descriptive statistics on the variables considered in this study during the period from 2020 to 2024. Descriptive statistics focus solely on the mean, minimum, maximum, and standard deviation values.

Table 2. Descriptive statistics.

Indicators	Trade	AI	GDP	INF	EX
Mean	-5.0335	32.1150	3.1627	25.3019	1371.886
Maximum	29.4299	53.94	4.5894	667.63	27445.3
Minimum	-35.3192	20.22	-20.8053	-0.7728	5.6
Std. dev	14.0652	7.4439	4.5894	85.5307	3290.647
Observations	185	185	185	185	185

The results presented in Table 2 show that the mean values of Trade, AI, GDP, INF, and EX are -5.034, 32.115, 3.163, 25.302, and 1371.886, respectively. The minimum values are -35.319, 20.22, -20.805, -0.773, and 5.6, while the maximum values are 29.429, 53.94, 4.589, 667.63, and 27445.3. In addition, it is important to mention that the greatest variability in the variables, as indicated by standard deviation, was recorded by the exchange rate (EX) at a value of 3290.647, followed by inflation (INF) at a value of 85.531. The variable with the least variability is gross domestic product (GDP) at a value of 4.589.

4.2. Correlation Analysis

The results of the correlation analysis are presented in Table 3, demonstrating the nature of the correlation between the variables considered in this study. In pairwise correlation analysis, collinearity may exist when the correlation value is high. According to the rule of thumb, when the absolute value of the pairwise correlation coefficient exceeds ±0.8, this suggests a potential collinearity risk.

Table 3. Pairwise correlation analysis.

Variables	Trade	AI	GDP	INF	EX
Trade	1.0000				
AI	-0.1189	1.0000			
GDP	-0.0306	0.0299	1.000		
INF	0.0009	-0.1123	-0.1710	1.000	
EX	-0.0112	-0.2231	0.0804	0.0726	1.0000

The results presented in Table 3 show a mixed correlation between the dependent variable and explanatory variables. There is a negative correlation between trade and every other variable except inflation (INF). Additionally, to address the issue of multicollinearity, the independent variables were checked for high levels of correlation. Based on the correlation coefficient values of the explanatory variables, none of the variables have a value higher than ±0.8. Therefore, the independent variables do not exhibit high correlation. The correlation coefficient values of these variables indicate a weak correlation; this implies that the explanatory variables in this study do not move closely together. This weak correlation between the variables could be a result of the short time periods considered in this study.

4.3. Unit Root Test

Gujarati and Porter (2010) argue that, to ensure appropriateness and prevent spurious regression in a dynamic panel inference, the stationary features are crucial. Thus, as a precondition for the model estimation, the Fisher ADF panel unit root test is employed to assess the stationary properties. This test is used in this study based on its advantage that it does not require a balanced panel, as in the case of the Im, Pesaran, and Shin (IPS) test (Maddala & Wu, 1999). Table 4 presents the Fisher ADF panel unit root test results.

Table 4. Fisher ADF panel unit root test results.

Variables	Inverse chi-square	Inverse normal	Inverse logit	Modified Inverse chi-square	Conclusion	Order of integration
Trade	171.5239***	-7.1944***	-7.1364***	8.0164***	Reject H_0	I(0)
AI	143.1042***	-5.8278***	-5.5864***	5.6803***	Reject H_0	I(0)
GDP	305.5333***	-12.3568***	-13.6690***	19.0319***	Reject H_0	I(0)
INF	154.7989***	-6.9217***	-6.5304***	6.6416***	Reject H_0	I(0)
EX	102.9047**	-1.6030**	-1.2061	2.3760***	Reject H_0	I(0)

Note: *** and ** at 1% and5% level of significance, respectively.

Table 4 illustrates that all the variables considered in this study are significant at the 1% and 5% levels of significance. This implies that all the variables are stationary in levels. As a result, it can be concluded that all the variables are integrated of order zero, I(0). The next step is to examine cointegration, as the variables have been integrated in the same order. Section 4.4 presents the cointegration test results.

4.4. Cointegration Test

Since all the variables are integrated into the same order, it is important to conduct a cointegration test to detect whether a long-run relationship exists between the variables considered in this study. The Westerlund cointegration test is adopted to conduct this analysis.

Table 5. Westerlund cointegration test.

Test	t-statistics	p-value
Variance ratio	218.1595	0.0000***

Note: *** at 1% level of significance.

The results presented in Table 5 suggest that the null hypothesis of no cointegration is rejected at the 1% level of significance. As a result, it can be concluded that the variables considered in this study are cointegrated and a long-term relationship exists between them. After establishing the cointegration test results, the subsequent step is to compute the panel OLS model. Section 4.5 provides the residual diagnostic results obtained from the panel OLS model.

4.5. Panel OLS Diagnostics

Before estimating the GMM, it is crucial to assess the panel residual diagnostics tests as a prerequisite for model estimation (Deka & Cavusoglu, 2022). Thus, the purpose of estimating the OLS model is to confirm its residual diagnostics results. The results of panel OLS diagnostics tests are presented in Table 6.

Table 6 displays the results from the panel OLS model. The results obtained from this model demonstrate that all regressors have an insignificant impact on international trade, as none of the probability values are less than the significance levels of 1%, 5%, and 10%. This suggests that the estimates obtained from this model are unreliable. Additionally, the R^2 and Adjusted R^2 of this model are extremely low, at 3.09% and 0.9%, indicating poor goodness of fit. The F-statistic is also insignificant, implying that the overall model is not statistically significant. That is, the model does not explain a significant portion of the variation in the dependent variable. Furthermore, the residual diagnostic results show that heteroskedasticity is statistically significant at the 1% level of significance. This indicates that the model suffers from heteroskedasticity issues.

Table 6. Panel OLS diagnostics results.

Dependent variable: Trade				
Variable	**Coefficient**	**St. Err**	**t-statistic**	**p. value**
AI	-0.1963	0.1447	-1.3568	0.1766
GDP	-0.1648	0.2391	-0.6894	0.4915
INF	-0.0096	0.0205	-0.4705	0.6385
EX	0.0010	0.0006	1.5767	0.1167
	t-statistic			
R^2	0.0309			
Adjusted R^2	0.0090			
F-statistic	1.4113			
Jarque–Bera	0.0133			
Heteroskedasticity	206.2169***			
Residual cross-section dependence test				
Pesaran scaled LM	11.3331***			
Breusch–Pagan LM	1079.620***			
Pesaran CD	2.7532**			

Note: *** and ** at 1% and 5% level of significance, respectively.

The normality test, however, is statistically insignificant, implying that the model does not suffer from normality issues. Nonetheless, all cross-section dependence tests were statistically significant at the 1% and 5% levels of significance, indicating that the model suffers from cross-section dependence issues. Therefore, a more robust model capable of handling heteroskedasticity and cross-section dependence should be employed for more reliable estimates. Section 4.6 presents the results of Generalized Method of Moments (GMM) estimation.

4.6. The Generalized Method of Moments (GMM) Estimation

The Generalized Method of Moments (GMM) is conducted to detect the effect of artificial intelligence on international trade in 37 Sub-Saharan African economies. In this study, the GMM is conducted using the two-step GMM estimator. Table 7 provides the two-step GMM results.

Table 7. Two-step GMM estimates.

Dependent variable: Trade				
Variables	**Coefficient**	**St. Err**	**t-statistic**	**p. value**
Lag trade	0.7776	0.1226	6.34	0.000***
AI	0.1205	0.0705	1.71	0.096*
GDP	-0.2027	0.0800	-2.53	0.016**
INF	0.0035	0.0015	2.33	0.025**
EX	0.0000	0.0000	0.30	0.768
Constant	-4.6631	2.6882	-1.73	0.091*
	p. value			
F-statistic	15.28***			
AR (1)	0.060			
AR (2)	0.779			
Hansen test	0.562			

Note: ***, ** and * at 1%, 5% and 10% level of significance, respectively.

Table 7 exhibits the two-step GMM estimates of Eq. 3. Before proceeding with a deeper exploration of the computed results, numerous diagnostic and specification tests are conducted to guarantee the efficiency and reliability of the results. First, the Fisher test (F-statistic) is considered, and it exhibits a joint statistical significance of the estimated coefficients. Second, the Arellano and Bond (1991) test for serial correlation shows no evidence of second-order serial correlation, as the AR(2) is statistically insignificant. As a result, we fail to reject the null hypothesis of no second-order serial correlation in the computed GMM estimates. Third, the Hansen test is statistically insignificant, suggesting that the instrument is suitable for the system GMM model. According to Ifediora et al., (2022), the general guidelines for applying the Hansen test over-identification restriction (OIR) test are that the number of instruments must be lower than the number of groups. As a result, diagnostic and specification tests demonstrate the credibility of the GMM coefficients, indicating that it is more appropriate to base inference on the system GMM coefficients.

The results presented in Table 7 show that the lag trade coefficient is positive and statistically significant at a 1% level of significance. This implies that approximately 77.76% of the previous period's value of the dependent variable carries over to the current period. Moreover, this indicates that the past trade level significantly affects the current trade level in selected Sub-Saharan African countries. Table 7 also demonstrates that artificial intelligence has a positive and statistically significant effect on international trade at the 10% level of significance in selected Sub-Saharan African countries. This suggests that a 1-unit increase in artificial intelligence capability is associated with a 0.1205-unit increase in the international trade level in Sub-Saharan African countries, *ceteris paribus.* The economic implications of this finding are that the artificial intelligence readiness of a country influences its trade levels. This establishes that investment in artificial intelligence may stimulate trade in Sub-Saharan African countries. This finding corroborates the results observed in the studies of Jayathilaka (2022) and Qian and Lai (2024). Furthermore, this aligns with the views of the Neo-technology theory of international trade and the Technology Acceptance Model (TAM). The TAM emphasizes that the acceptance of technology like AI in various sectors, including the trading sector, can support the refinement of trading processes and outcomes. Additionally, the Neo-technology theory of international trade proposes that technology such as AI is a determinant of international trade.

The results further show that GDP has a negative and statistically significant influence on international trade at the 5% level of significance. This means that a 1-unit rise in GDP is correlated with a 0.2027-unit reduction in the international trade level in Sub-Saharan African countries, *ceteris paribus.* The economic implication associated with this finding is that the GDP of a country has a significant negative influence on the international trade level in Sub-Saharan African countries. This could suggest that higher local output is linked with improved import demand that offsets export gains, hence international trade worsens. Moreover, most Sub-Saharan African countries are import-dependent economies; this could be the reason for the negative impact of GDP on international trade. Although this result does not align with economic theory, a negative coefficient of GDP was also established by Qian and Lai (2024) in one of their estimated models. Qian and Lai (2024) conducted a study on 139 developing and developed countries, and in one of their models, the results show that GDP has a negative relationship with trade. However, this result does not align with the findings of Jayathilaka (2022); this could be associated with the use of different study periods and countries of focus. Interestingly, the results show that inflation (INF) has a positive and statistically significant influence on international trade at the 5% level of significance. This means that a 1-unit rise in inflation is correlated with a 0.0035-unit increase in the international trade level in Sub-Saharan African countries, *ceteris paribus.* This finding aligns with the purchasing power parity (PPP) on the basis that inflation influences international trade through imports and exports. According to PPP, high local prices lead to an increase in imports and a decrease in exports, consequently affecting international trade. This finding departs from the findings obtained by Jayathilaka (2022), and this could be attributed to the use of different study periods and estimation techniques. Nonetheless, this finding suggests that inflation exerts an impact on the international trade level in Sub-Saharan African countries. Unexpectedly, the exchange rate is found to exert a positive and statistically insignificant impact on international trade. This implies that the exchange rate has little to no influence on the international trade level in Sub-Saharan African countries.

5. CONCLUSION AND POLICY RECOMMENDATION

This study examined the effect of artificial intelligence on international trade in selected Sub-Saharan Africa for the period from 2020 to 2024. The examination was conducted utilizing the Generalized Method of Moments (GMM) to fit a short time span. The findings confirm that artificial intelligence and inflation have a positive and statistically significant influence on international trade in the Sub-Saharan African countries. Moreover, GDP has an inverse and statistically significant effect on international trade. Nevertheless, the exchange rate exerts no influence on international trade in the Sub-Saharan African countries. This study concludes that artificial intelligence, inflation, and GDP influence international trade in selected Sub-Saharan African countries.

The evidence on the relationship between international trade and artificial intelligence is primarily found in conceptual and systematic review studies, with limited empirical evidence available. This study addresses the gap in the body of literature on international trade and artificial intelligence. The findings contribute to the current literature on the nexus between artificial intelligence and international trade by empirically evaluating the effect of artificial intelligence on international trade in selected Sub-Saharan African countries. Furthermore, this study provides evidence for additional variables besides artificial intelligence that influence international trade levels in these countries.

The findings here represent important guidelines that governments of the sampled nations are recommended to follow and implement in shaping their economic policies. First, this study advocates for the adoption and application of AI technology to stimulate trade. Investing in artificial intelligence technology not only boosts trade but benefits the people, entrepreneurs, and companies at large. Artificial intelligence technology may also augment market access by supporting companies to better realize demand trends and detect new international opportunities. Second, governments may consider reviewing policies and regulations in the trading sector to fit the adoption and application of artificial intelligence in this sector. This may reinforce global trade governance and accelerate globalization. Third, governments should consider raising awareness about the incorporation of artificial intelligence in trading, as it is vital for enabling the sector's growth and ensuring that artificial intelligence technologies are employed effectively and ethically. By concentrating on raising awareness of the usage of artificial intelligence in trading, it could help bridge information gaps, thus improving efficiency in international trade. Lastly, when formulating policies to fit AI, policymakers should take note of other factors affecting international trade such as GDP and inflation.

While this study offers valuable observations into the impact of artificial intelligence on international trade, it is limited to a short time span; therefore, it is recommended that further research on the impact of artificial intelligence on international trade consider using an extended time span. Moreover, further research should investigate this topic at a country level as opposed to a panel of countries. This study is limited by using a few independent variables to explain international trade; therefore, future studies should consider including trade policy changes, terms of trade, trade restrictions, regional integration agreements, or commodity price shocks as independent variables in their models.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all ethics processes.
Data Availability Statement: Upon a reasonable request, the corresponding author can provide the supporting data of this study.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

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