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An Investigation of the Impact of Artificial Intelligence on Financial Inclusion in Developing Economies: Case of Sub-Saharan Africa

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Abstract

The main aim of the study was to investigate the impacts of artificial intelligence (AI) on financial inclusion in developing economies drawing evidence from the Sub-Saharan African (SSA) region. The specific objectives were to determine existence of a long-run relationship between artificial intelligence and financial inclusion and to establish causality between artificial intelligence. The study employed the quantitative approach and explanatory research design. Panel data from a convenience sample of 43 Sub-Saharan African countries for the period from 2019 to 2023 was gathered from various secondary sources. The autoregressive distributed lag model was estimated basing on the Generalized Method of Moments technique. The study revealed a significant positive effect of artificial intelligence on financial inclusion. The study further revealed a significant positive long-run and bi-directional relationship between artificial intelligence and financial inclusion. The study concluded that artificial intelligence plays an important role in driving financial inclusion in this era of digitalization. The study recommended governments in the SSA region in the region to increasingly invest in developing and expanding technological infrastructure particularly in underserved or remote areas such as rural areas to promote adoption of artificial technologies for realization of increased financial inclusion.

Keywords: Financial inclusion, Artificial intelligence, Sub-Sahara Africa

1. Introduction

Financial inclusion (FI) has been considered crucial towards attainment of inclusive sustainable economy growth in low-and-middle-income countries (LMICs) (Arakpogun et al., 2021). Hence, enhancing FI has increasingly become central in the persisting debate on how to ensure that marginalized population become financially active (Mhlanga, 2020). However, over the past years, low FI has been a global concern where the World Bank's (2023) report showed that nearly 50% of the world's adult population or about 3.5 billion people across the globe are underbanked and unbanked implying no or limited access to formal finance. On the other hand, the World Bank (2023) reported that more than 200 million businesses in LMICs across the globe lack access formal financial products and services. The low levels of financial inclusion have been a global concern and have been linked to the stagnation of economic growth in LMICs across the globe (Demirgüç-Kunt et al., 2020).

Recently, digital technologies such as artificial intelligence (AI) and machine learning (ML) have been rapidly transforming economies across the globe by facilitating financial inclusion (Arakpogun et al., 2021; Mpofu & Mhlanga, 2022). Precisely, Kshetri (2021) reported that AI-based solutions have emerged as the socio-economic game-changer with significant implications for expanding accessibility to financial products and services in developing economies. The importance of digital technologies such as AI gained prominence following the emergency of COVID-19 pandemic which forced governments and institutions to give a careful thought to adoption of AI (Hassan, 2024). Since then, AI has been considered an important tool for enhancing financial inclusion (Demirgüç-Kunt et al., 2020).

In Africa, digital technologies such as artificial intelligence have also gained prominence particularly in the Sub-Sahara Africa (SSA) region as drivers for financial inclusion (Maouloud et al., 2022; Vibbi, 2024). According to Hassan (2024), adopting and incorporating AI into the financial sector has become imperative for driving financial inclusion towards achievement of the critical sustainable development goals (SDGs) in African developing economies. For instance, the use of AI particular the chatbot known as Leo by the United Banking for Africa in Nigeria and the Safaricom's chatbot in Kenya have been found to be driving FI in the country (Dirie, 2024). Similarly, the utilization of AI technologies by South African banks such as TymeBank has been found contributing to increased access to financial services (Kshetri, 2021).

There is strong support from empirical evidence that adoption and use of digital technologies such as AI can help in driving FI in African developing economies by addressing barriers to financial access information asymmetry (Maouloud et al., 2022; Mhlanga, 2020). Other studies also support that digital technologies such as AI can significantly drive financial inclusion (Mallick & Chakraborty, 2024; Sinha et al., 2023; Subramaniam et al., 2024). Whilst there is evidence that the rate at which FI is rising due to adoption of digital technologies such as AI (Chibesa & Mwange, 2025; Mwange & Mumba, 2025), there is limited empirical evidence confirming the link between AI and FI. Hence, the need for this research to investigate the impacts of AI on FI in the context of developing economies in SSA. This research is motivated by two fundamental factors: (i) the trends in AI and FI in SSA and (ii) lack of comprehensive and convincing existing empirical literature in the context of SSA developing economies.

2. Review of Related Literature

2.1. Theoretical framework

The main theory forming the theoretical framework for the study is the digital agency theory of FI developed by Ozili (2024b). The theory states that financial inclusion principals (financial institutions) employ services of digital agents (Fintech firms) who utilise appropriate digital financial technologies to achieve financial inclusion outcomes (Ozili, 2024b). In other words, the theory is all about the connection between FI principals and digital agents who accelerate FI using applicable digital technologies.

According to Ozili (2024b), the digital agency theory of FI has broad applicability in digital financial inclusion discourse. This theory complements other existing models and theories such as the technology impact model, the special agent theory of FI and the systems theory of FI (Ozili, 2020a; 2024b). The digital agency theory of FI as propounded by Ozili (2024b) attempts to show how digital agents and technologies can accelerate usage and access to formal financial products or services by those in need of them. Hence, the theory was deemed fitting to help in explain the impacts of AI on financial inclusion.

2.2. Role of artificial intelligence in financial inclusion

Artificial intelligence has been found to have significant applications and benefits which lead to increased financial inclusion (Chadha & Gupta, 2024). As cited by Sinha et al. (2023), AI promotes financial inclusion as it can inform financial decision-making of individuals and businesses. For instance, AI-powered platforms such as Robo-Advisors provide automated financial investment advice which can aid in financial inclusion decision-making (Dai, 2021). Tram et al. (2023) also showed that AI can also be used by financial institutions in making informed lending decisions and decisions to expand credit to individuals and businesses thereby helping in driving financial inclusion. According to Aziz and Andriansyah (2023), AI can expedite FI by enabling the delivery of personalized financial products and services tailored to meet the financial needs of individuals and businesses.

The study by Sinha et al. (2023) also revealed the role of AI in promoting FI arguing that AI leads to enhanced accessibility to financial products and services. Besides enhancing accessibility, Hassan (2024) reported that AI can promote financial inclusion by overcoming the problem of information asymmetry which leads to financial exclusion. Mallick and Chakraborty (2024) also cited that AI can augment FI by helping financial institutions to progressively gain customers' confidence and trust through enhanced fraud detection and cyber security. Equally, Adeoye et al. (2024) reported that leveraging AI presents a promising avenue for advancing FI and addressing financial exclusion in LMICs. Yasir et al. (2022) also supports the arguments that AI applications aids removing barriers to FI.

From the existing literature, there is strong support that AI can drive financial inclusion. However, AI can also have adverse impacts on financial inclusion. For instance, Boukherouaa et al. (2021) and Yanting and Ali (2021) also argued that whilst AI can deepen FI it also poses risks such as widening the digital divide between developing and advanced economies. Ozili (2024a) also argued that there are risks of digital technologies which inhibit financial inclusion as digital

technologies such as AI reinforce inequalities as well as worsening the welfare of the poor people leading to the financial inclusion-exclusion paradox. In addition, Ozili (2024b) contended that digital financial inclusion may be difficult to achieve given uneven accessibility and availability of digital technologies.
From the aforementioned discussion and review of literature, several empirical studies have been conducted to determine the impacts of AI on FI. The existing empirical literature is summarized in Table 1.

Table 1: Summary of empirical studies

Author(s) and year	Aim/objectives	Methodology/ Research design	Main Findings/Conclusions
Subramaniam *et al.* (2024)	Relationship between AI and FI	Quantitative design using dynamic and statistic GMM panel regression for a sample of 29 countries (2017-2021)	AI is a statistically significant predictor of FI
Sinha *et al.* (2023)	Impacts of AI on digital FI in India	Qualitative design based on systematic literature review	AI plays a significant role in promoting FI
Maouloud *et al.* (2022)	Role of AI in accelerating FI in African economies	Qualitative design based on systematic literature review	AI plays a significant role in expediting FI
Fazal *et al.* (2023)	Relationship between FI and AI	Qualitative systematic review methodology	Significant importance of AI in promoting financial inclusion
Fazal *et al.* (2024)	Importance of AI in achieving SDGs through FI	Qualitative desk research methodology	AI is indispensable for driving FI
Adeoye *et al.* (2024)	Impact of AI technologies on financial inclusion	Qualitative literature review methodology	AI technologies significantly promote FI
Chadha and Gupta (2024)	Impact of AI on financial inclusion	Qualitative literature review methodology	AI technologies significantly promote FI
Kshetri (2021)	Role of AI in promoting FI in LMICs	Qualitative literature review methodology	AI technologies significantly promote FI
Mallick and Chakraborty (2024)	Integration of AI in digital FI	Qualitative literature review methodology	AI has significant role in promoting FI
Mhlanga (2020)	Impacts of AI on digital FI	Qualitative desk research methodology	AI has strong influence on digital FI

Source: Authors

2.3. Conceptual Model

The conceptual framework shown in Figure 1 depicts the hypothesized associations between artificial intelligence, financial inclusion and control variables.

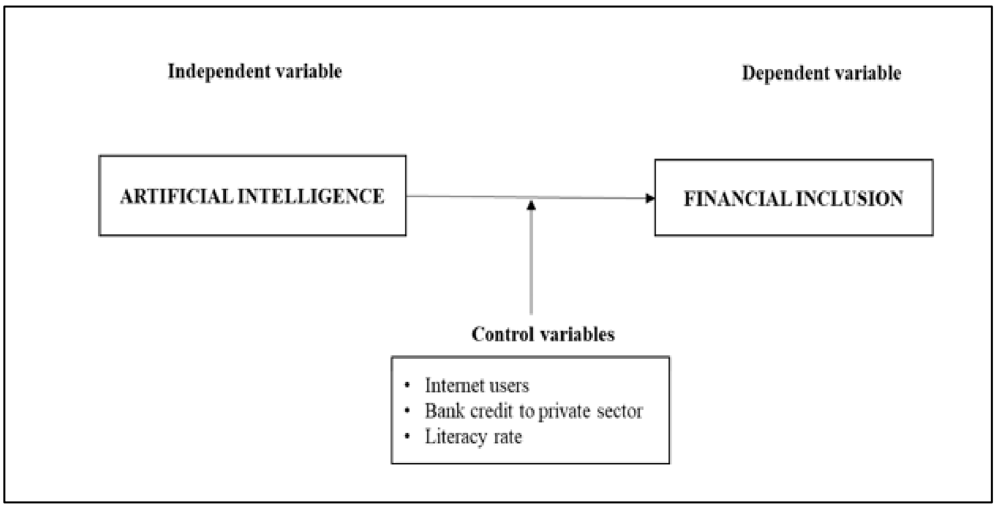

Figure 1: Conceptual framework (Source: Own compilation)

3. Methodology

3.1 Research approach

The quantitative research approach was adopted given the quantitative nature of the research topic and objectives. The quantitative research approach was found the most suitable in this study which sought to determine the impacts of AI on financial inclusion in SSA. The quantitative research approach also permitted hypothesis testing in this study.

3.2 Research design

This study employed the explanatory research design given the quantitative nature of the research. The explanatory research design suitable for quantitative researches that seek to investigate cause-and-effect relationships between variables (Creswell & Creswell, 2022). The main objective of this research design is to establish causal relationships between dependent and independent variables as well as potential control or moderating variables (Asenahabi, 2019). The explanatory research design was found the most appropriate research design for this study which attempt to analyse the impacts of artificial intelligence and financial inclusion.

3.3 Sample

The study's sample was drawn from the population of 48 countries from the SSA region (World Bank, 2024). The convenience sampling technique was employed to select SSA countries with readily available data on AI and FI. Basing on this sampling technique, 43 SSA countries were included in the sample based on data availability. Five countries namely Eritrea, Sao Tome and Principe, Equatorial Guinea, Somalia and South Sudan were excluded for lacking data on AI and other variables. In addition, the sample time period was five years (2019-2023).

3.4 Model specification

In line with previous empirical studies (such as Subramaniam et al., 2024), the following ARDL logarithmic econometric panel regression model for the impacts of AI on FI was developed:

$$lnFI_{it} = \beta_0 + \beta_1 lnFI_{it-1} + \beta_2 lnAI_{it} + \beta_3 lnLR_{it} + \beta_4 lnCPS_{it} + \beta_5 lnIU_{it} + \beta_6 lnEG_{it} + \gamma_i + \mu_{it}$$

Where;

FI_{it} = Financial inclusion measured the number of deposit account ownership with commercial banks per 1,000 adults in country *i* at time *t*

FI_{it-1} = Financial inclusion measured the number of deposit account ownership with commercial banks per 1,000 adults in country *i* at time *t* lagged by one period controlling for potential persistence changes in financial inclusion

AI_{it} = Artificial intelligence for country *i* at time *t* measured by government AI Readiness Index LR_{it} = Literacy rate for country *i* at time *t* measured by the ratio of literate citizens aged from 15 years

CPS_{it} = Domestic credit to the private sector from formal financial institutions (% of GDP) for country *i* at time *t*

IU_{it} = Internet usage for country *i* at time *t* measured by the number of Internet users as a percent of total population

EG_{it} = Economic growth for country *i* at time *t* measured by GDP per capita in United States dollar (US$)

μ_{it} = random error term with constant variance and zero mean

γ_i = country fixed effects to eliminate unobserved country-specific characteristics which could affect the relationship between AI and financial inclusion.

β_0 = regression intercept;

β_1 to β_6 = regression coefficients;

ln = natural logarithm;

t = time period from 2019 to 2023

The logarithmic equation aids in addressing non-normality of data as argued by Watson and Stock (2020). Moreover, the study followed the ARDL model noticing that change of the financial inclusion index can be persistent over time such that lagged dependent variable (〖lnFI〗 _(it-1)) would improve the model. Table 2 provides the summary of operationalization of the key variables.

Table 2: Operationalization and measurement of variables

Variable	Notation	Variable type	Indicator/Measure	Data source
Financial inclusion	FI	Dependent variable	Number of deposit account ownership with commercial banks per 1,000 adults	World Bank
Artificial intelligence	AI	Independent variable	Government AI Readiness Index	Oxford Insights and IMF

Literacy rate	LR	Control variable	Adult literacy rate measured by ratio of literate citizens aged from 15 years	World Bank and UNESCO Institute for Statistics
Credit to private sector	CPS	Control variable	Bank credit to the private sector as percent of GDP	World Bank
Internet users	IU	Control variable	Internet users as a percent of total population	World Bank
Economic growth	EG	Control variable	GDP per capita in US$	World Bank

Source: Own compilation

3.5 Data sources

To fulfil the objectives of the study, the study employed annual panel data for the five-year period from 2019 to 2023. This period was chosen given it is the period witnessed by the increased intentions to embrace artificial intelligence following emergence of the Covid-19 pandemic (Oxford Insights, 2023). Secondary data sources were targeted. The main sources for data were the World Bank Development Indicators (WDI), UNESCO Institute for Statistics, Oxford Insights, World Bank's Global Findex database and IMF.

3.6 Data analysis

The study employed ARDL panel regression model based on the GMM technique to analyze the data. The GMM aided in addressing the endogeneity and multicollinearity problem in the model as observed by Greene (2018). The GMM technique was also employed by Subramaniam et al. (2024) arguing the existence of potential endogeneity between financial inclusion and AI. The GMM technique also aided in address the issue of possible endogeneity emerging from the association between present and past values of the predicted variable (FI). Furthermore, the two-stage system GMM estimator was preferred compared to the difference GMM estimator as the two-system GMM estimator corrects for cross-section dependency prevalent characteristic in panel data regression (Wooldridge, 2015).

E-views version 13 was employed as the data analysis software. Descriptive statistics were also employed to summarize and provide a general trend of the dataset. Pre- and post-estimation tests such as unit root tests, Hausman test, multicollinearity test, autocorrelation test and normality test were done to enhance robustness of the results as well as avoiding spurious regression. The study further employed the Johansen co-integration test to determine the existence of a long-run relationship between AI and FI using the Kao Residual Co-integration Test for panel data. The study also carried out the granger causality to determine causality between financial inclusion and AI.

4. Results and Discussion

4.1 Descriptive statistics

Table 2 reports the descriptive statistics for the variables employed in the study using raw data.

Table 2: Descriptive statistics

Statistic	FI	AI	CPS	EG	IU	LR
Mean	505.01	32.12	23.98	2366.99	36.44	66.21
Median	271.86	29.84	17.53	1193.36	32.55	67.03
Maximum	3637.54	267.23	145.39	19141.51	83.83	96.20
Minimum	71.37	19.30	0.01	199.58	2.73	25.11
Std. Dev.	633.00	17.61	22.36	3117.14	20.08	19.01
Skewness	2.84	11.18	2.97	2.98	0.57	-0.34
Kurtosis	11.88	149.21	13.73	12.98	2.26	2.08
Jarque-Bera	995.93	195978.70	1347.07	1210.20	16.36	11.80
Probability	0.00	0.00	0.00	0.00	0.00	0.00
Sum	108576.70	6906.45	5156.50	508902.90	7835.27	14235.36
Observations	215	215	215	215	215	215

The mean of 505.01 for FI reported in Table 2 show that the average number of deposit accounts for commercial banks in SSA countries for the period 2019 to 2020 was about 505 per 1,000 adults. This implies that about 50% of the individuals in the SSA region were financially included for the period between 2019 and 2023.

More so, the mean statistic of 32.12 for AI show that on average the government AI readiness index for the SSA region is approximately 32.12 whilst highest index and lowest index recorded for the region were 267.23 and 19.30. This is in line the average government AI readiness index of 30.16 for the entire SSA region provided by Oxford Insights (2023).

4.2 Unit root tests results

Prior to the estimations of ARDL-GMM regression model, the study carried out panel unit root tests for all the variables using the ADF, LLC and PP tests. The results from the panel unit root tests are reported in Table 3.

Table 3: Panel unit root test results

Variable	LLC		ADF		PP		Order of integration
	Level	1st diff.	Level	1st diff.	Level	1st diff.	
*ln*FI	-3.7***	-97.1***	-66.25	215.2***	75.8	247.8***	I (1)
*ln*AI	-14.5***	-22.1***	76.5	116.1***	86.0	139.4****	I (1)
*ln*IU	-14.2***		263.1***		383.5***		I (0)
*ln*LR	-48.2***		132.5***		168.3***		I (0)
*ln*CPS	-7.5***	-142.4***	74.6	161.7***	95.5	197.8***	I (1)
*ln*EG	-4.1***	-1462.1***	67.9	194.2***	81.4	228.3***	I (1)

Note: ** means statistically significant at 5% level

From the LLC, PP and ADF test results reported in Table 3, only two series were found to have no unit roots at level for variables two namely lnIU and lnLR. Hence, these were integrated of order zero [I(0)]. The other four variables (lnFI, lnAI, lnCPS and lnEG) were found to have unit roots at level such that they were differenced to make them stationary. In this essence, the four variables were I(1).

4.3 Hausman test results

The Hausman test showed a Chi-square statistic of 0.44 with a p-value of 0.9985 implying that the RE model was the most appropriate panel regression model to estimate the impacts of AI on FI in the SSA region.

4.4 Results of the panel ARDL-GMM regression model

The results of the ARDL regression model based on the GMM technique are reported in Table 4.

Table 4: ARDL-GMM regression results (Dependent variable: Financial inclusion)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.684965	0.328562	8.171865	0.0000***
d*ln*AI	1.062438	0.113000	9.402071	0.0000***
*ln*IU	0.162222	0.017779	9.124586	0.0000***
*ln*LR	0.090675	0.019368	4.681804	0.0000***
d*ln*CPS	0.021355	0.004240	5.036209	0.0000***
d*ln*EG	0.183864	0.050078	3.671548	0.0004***
d*ln*FI(-1)	1.224772	0.059803	20.48024	0.0000***
R-squared	0.865000	Mean dependent var		2.631225
Adjusted R-squared	0.858360	S.D. dependent var		0.402477
S.E. of regression	0.151473	Sum squared resid		2.799160
Durbin-Watson stat	2.327386	J-statistic		4.21E-18
Instrument rank	7			

NB: * ** means statistically significant at 5% level

As revealed in Table 4, the R2 of 0.865 showing that about 86.5% of the variations in financial inclusivity jointly explained by AI and the included control variables. This indicates goodness-of-fit in the estimated ARDL model whilst the remaining 13.5% accounts for variations caused by other factors not included in the model.

From the results in Table 4, all the variables were found to be statistically significant at 5% level. The estimated ARDL regression model was therefore presented as follows:

$$FI_{it} = 2.68 + 1.22(FI_{it-1}) + 1.06(AI_{it}) + 0.16(IU_{it}) + 0.09(LR_{it}) + 0.02(CPS_t) + 0.12(EG_{it})$$

4.5 Co-integration test results

The results of the panel Kao residual co-integration test are reported in Table 5.

Table 5: Co-integration test results

		t-Statistic	Prob.
ADF		-8.908947	0.0000***
Residual variance		0.000380	
HAC variance		0.000432	

NB: * ** means statistically significant at 5% level

The Kao co-integration results reported in Table 5 show that the ADF t-statistic of -8.91 with a corresponding p-value of 0.0000 indicate that existence of a significant long-run relationship between AI and FI in the SSA region.

4.6 Granger causality test results

The results of the Granger causality test are outlined in Table 5.

Table 5: Granger causality test results

Null Hypothesis:	Obs.	F-Statistic	Prob.
d*ln*FI does not Granger Cause d*ln*AI	86	4.23	0.0178***
d*ln*AI does not Granger Cause d*ln*FI		3.47	0.0359***

NB: * ** means statistically significant at 5% level

The results presented in Table 5 show existence of a bi-directional causal relationship between AI and FI in the SSA region as indicated by the p-values less than 0.05.

These results clearly show that AI adoption can significantly drive and promote financial inclusion in the SSA region. The study therefore failed to accept the null hypothesis that artificial intelligence has no significant positive impacts on financial inclusion. In addition, the co-integration results confirmed existence of a long-run relationship implying that AI can significantly drive financial inclusion in SSA developing countries in the long-run. The results confirm the findings from the research by Sinha et al. (2023) and Subramaniam et al. (2024) which found a significant positive relationship between AI and FI. The findings also confirm the direct positive relationship predicted by the Ozili's (2024a) digital agency theory of FI.

5. Conclusions, Implications and Recommendations

5.1 Conclusions

The overarching conclusion reached is that there exists a significant positive long-run and bi-directional relationship between artificial intelligence and financial inclusion. In addition, the study's empirical results shed light on the intricate interplay between AI, economic growth, literacy rate, Internet usage and credit provided to the private sector in enhancing financial inclusion in developing SSA economies. In short, it can be concluded that adoption of digital technologies such as AI in developing economies in the SSA region stands out as a driving force in the quest for enhancing FI towards attaining inclusive sustainable economic growth. With reference to the study's empirical results, it can also be concluded that AI plays an important role in driving FI in the SSA region in this era of digitalization.

5.2 Recommendations and implications

The empirical results proved to have significant implications for policy and practice. Hence, the following recommendations were made:

1. The study recommends governments of the SSA countries to increasingly invest in developing and expanding technological infrastructure particularly in underserved or remote areas such as rural areas. This will eventually enhance adoption of AI which further promote increased accessibility to financial products and services thereby promoting financial inclusion.
2. The research also recommends governments and financial institutions across the SSA region to leverage on AI and scale up the adoption and utilization of AI applications and tools by the financially excluded individuals through initiatives such as awareness programs.
3. The study also recommends governments in the SSA region to put in place policies that promote adoption of AI-based technologies. This will create a conducive environment for financial institutions to invest in AI technologies which enhance access to financial products and services thereby enhancing financial inclusion.

5.3 Limitations and areas for further research

The study had its own unique limitations which represent gaps for further study. Firstly, the study only focused on countries from the SSA region such that the results lack applicability and generalizability to other regions or the entire African continent. Hence, further research can be done focusing on other regions other than the SSA region. Furthermore, the study only employed one indicator of FI whilst there are several indicators or measures of FI obtained from the World Bank's Global Findex database. Other similar studies may also consider employing different indicators to enhance robustness of the results on the impacts of AI on FI.

Conflict of Interest

The authors declare that they have no conflicting interests

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Ethical considerations

The article followed all ethical standards appropriate for this kind of research.

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