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Harnessing Artificial Intelligence to Enhance Financial Inclusion: Insights from a Cross-Sectional Study

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Abstract: The rise of digital transformation has significantly contributed to financial development and economic growth. This study investigates the impact of artificial intelligence (AI) adoption on financial inclusion, examining how AI-driven solutions improve financial accessibility across economies with varying technological readiness levels. Using panel data from 35 countries between 2017 and 2023, we apply the Two-Stage Least Squares (TSLS) system and the Generalized Method of Moments (GMM) model to analyse the influence of artificial intelligence on financial inclusion indicators. This study underscores the vital role of AI in shaping the future of financial inclusion. The empirical evidence demonstrates that AI adoption enhances financial accessibility by overcoming traditional constraints, optimising risk assessment, and fostering innovation in financial services. The findings show that artificial intelligence adoption substantially and concretely impacts enhancing financial accessibility. Specifically, AI-driven solutions reduce barriers to banking services, increase digital financial participation, and expand access to credit, particularly in regions with robust technological infrastructure. Importantly, the positive effects are most significant in economies with supportive institutional and regulatory frameworks, highlighting the role of policy in amplifying artificial intelligence benefits. This study makes a unique contribution by linking artificial intelligence adoption to specific financial inclusion outcomes and highlighting the crucial role of institutional quality in maximising these benefits. The practical implications of these findings are far-reaching for policymakers and financial institutions. They underscore the need for integrated strategies that leverage AI innovations and ensure regulatory safeguards, promoting a more inclusive and sustainable financial ecosystem. These insights provide valuable implications for optimising AI-driven financial inclusion initiatives.

Keywords: Artificial Intelligence, Digital Financial Services, Dynamic GMM, Financial Inclusion.

Introduction

The third technology revolution has significantly accelerated digital transformation and provided technical support for artificial intelligence technologies, driving economic and social progress. The development of expert systems (Expert Syst), machine learning (ML) and big data analysis (BDA) are leading the fourth generation of industrialisation. Hence, artificial intelligence (AI) increasingly reshapes economic sectors, including the financial systems. Those leveraging technological applications, such as machine learning (ML) and big data analysis that bridge the financial gap can maintain financial stability through improved financial monitoring and risk mitigation (Tinta et al., 2022).

Artificial Intelligence technologies can detect abnormal patterns that indicate financial fraud or systematic threats early, permitting authorities to take preventive measures more efficiently. Using Artificial Intelligence in financial systems would reduce the costs of accessing financial services and provide them quickly, flexibly and securely (Adeoye et al., 2024). However, this rapid shift in AI adoption raises questions about potential challenges, including privacy, cyber security and digital inequality (Park & Mercado, 2018; Pradhan, 2023; Prasuna et al., 2024). Several countries need the development of digital infrastructure and technological skills to reduce financial exclusion. On the other hand, AI represents an unprecedented opportunity to redefine financial inclusion (FI) and financial stability. However, the success of this transformation depends on the extent to which countries can confront the accompanying challenges and leverage the potential of AI responsibly and comprehensively (Ali et al., 2016). The growth of the financial sector is related to the technological revolution led by digital transformation. Under the Global Findex database (DataBank, n.d.) and financial access survey (FAS) (IMF, 2024), digital payments and mobile transactions have spread in developing economies in recent years. Innovation in digital financial services (DFS) can support financial inclusion and eliminate financial exclusion by mobilising savings and providing access to and use financial services.

According to the World Bank, financial inclusion is the ability of individuals and businesses to access and use affordable financial products for transactions, payments, and insurance responsibly and sustainably. (DFS) are also crucial for generating data that can be used for decision-making, government efficiency, reducing financial exclusion, and maintaining policy implementation (DataBank, n.d.).

The Association of African Central Banks (AACB) launched the African Inter-Regional Payments Integration Task Force to promote financial inclusion in 2020. It established two working groups, the Payment Systems Integration Group and the Mobile Integration Strategy Group. Findings showed those broader initiatives could dismantle barriers and open digital financial services provision (World Bank Group, 2023). Additionally, the Central Bank of Indonesia has specifically launched the (DFS) initiative; this program is a payment system service carried out not through physical offices but with technological facilities, including mobile money and customer support (Triwibowo & Nurbasith, 2023).

Research Problem

A trend of researchers has emerged as contributions of Dirie (2024), Fazal and Ahmed (2023), Mhlanga (2020), and World Bank Group (2023), who believed that standards of the traditional financial inclusion must be developed and what is known as digital financial inclusion (DFI) has emerged that can keep pace which this unprecedented digital transformation, especially since the fuel of artificial intelligence is data analysis.

The banking, financial services and insurance (BFSI) sector is experiencing a growing adoption of technology through the analysis generated by AI and ML. Big data fuels artificial intelligence, which enhances valuable insights into available financial services and increases operational efficiency and risk hedging (Pattnaik et al., 2024).

Building upon this technological shift, the increasing adoption of AI in financial systems raises important research questions regarding its role in financial inclusion and stability. This study addresses several critical concerns, such as the need to reassess financial inclusion models, as traditional financial mechanisms may no longer be adequate to address contemporary financial stability challenges. Enhancing AI-driving financial inclusion can promote equitable access to financial services, reduce income disparities and foster sustainable economic growth. This study contributes to the literature by integrating AI into financial inclusion research, providing empirical insights into its impact, and proposing novel frameworks for evaluating financial accessibility. While existing research has explored AI in financial systems, it has not extensively examined its direct impact on financial inclusion. This contribution introduces an AI index variable to measure financial inclusion, filling a crucial research gap and comprehensively analysing AI's role in financial accessibility.

Research Focus

This research focuses on the role of AI in financial inclusion, investigating how AI-driven technologies influence financial accessibility and economic stability. By examining the intersection of AI and financial inclusion, the study aims to determine how AI adoption fosters or hinders financial access and stability in different economies.

Financial inclusion is an essential issue for the global agenda and for the sustainable development goals (SDGs). The author's scientific focus is on the accessibility issues for all individuals and organisations to formal financial services, whether in a developed or developing environment, including digital payments, insurance, savings accounts, and credit options. These facilities promote economic growth, poverty reduction, and income inequality (How et al., 2020; Le et al., 2019).

Research Aim and Research Questions

Our study addresses the research gap that previous studies have not yet studied the impact of adopting artificial intelligence on financial inclusion (Subramaniam et al., 2024). This is due to two main reasons: (1) the lack of a single multi-dimensional indicator that measures financial inclusion and (2) the failure to include the artificial intelligence index among the variables for estimating financial inclusion. In our study, we will add the artificial intelligence index variable that appeared for the first time in 2017.

The primary objective of this study is to assess the impact of AI adoption on financial inclusion, addressing the following research questions:

1. How does AI adoption influence financial inclusion across different economies?
2. What are the key determinants of financial inclusion in an AI-driven financial system?
3. How can policymakers leverage AI to enhance financial accessibility while mitigating associated risks?

This study employs an empirical approach to address these questions, analysing cross-sectional data from 35 countries between 2017 and 2023. Several macroeconomic variables are incorporated to enhance the robustness of the findings.

In this study, we review the literature and summarise existing literature gaps. Afterwards, we present the estimation model and data. Then, we deliver the estimation results and discuss further analysis. Finally, we conclude the paper and tender some policy suggestions.

Literature Review

The benefits of AI and ML in analysing big data and regulation technology are discussed in several papers, which are developing models for implementing technology in the (BFSI) sector. Financial inclusion is the only way to stay connected to the financial system in a pandemic or crisis (Fazal & Ahmed, 2023). The literature on the intersections between financial inclusion and artificial intelligence is divided into several key sections, each exploring different dimensions and aspects of the topic.

Financial Inclusion Indicators

Since 1990, the literature explained financial inclusion with economic factors. Thus, existing research has explored demand-side factors, which are microeconomic determinants such as financial market size, the level of the informal economy, education, and gender. Besides macroeconomic determinants, variables include economic stability, GDP per capita and telecommunication infrastructure (Nandru & Rentala, 2020). Other contributions such as Amoah et al. (2020), Camara and Tuesta (2018), Pesqué-Cela et al. (2021), Ravikumar (2020), and Tinta et al. (2022) also relied on demand-side factors such as income, gender, education, financial literacy. Barriers must be controlled, including restrictions on women and youth, financial services' geographic location, and bank costs (Ongo Nkoa & Song, 2020; Ozili, 2021; Stakić et al., 2021).

Financial inclusion measurements weighted by supply-side variables such as interest or inflation rates, mobile usage or Internet banking are not considered comprehensive measures since they cannot survey the individuals excluded from accessing or using financial services (Ben Khelifa et al., 2024). Furthermore, the institutional approach to defining financial inclusion composed the index of institutions' quality. Ali et al. (2016) studied 52 developing countries from 2004 to 2010 with the panel-GMM technique; they found that the absence of violence, government effectiveness, political stability, and regulatory quality increased financial inclusion.

Also, Orji et al. (2019) used quarterly data from 1986 to 2013, and applying the autoregressive distributed lag model based on an unrestricted error correction model, they found that institutional quality is positively related to financial inclusion in Nigeria. Chinoda and Kwenda (2019), using sys-GMM with panel data on 49 countries in 2004–2016, found a positive impact of institutional quality and governance on financial inclusion. Ongo Nkoa and Song (2020) estimated sys-GMM with a sample of 51 African countries from 2004–2018. Results show that institutional quality increases financial inclusion and the use and accessibility of financial services in Africa.

Artificial Intelligence Adoption

It is undeniable that technology has become mandatory in the world financial system and for achieving financial inclusion. Many impressive examples are M-Pesa in Kenya, which lifted the people from extreme poverty; the digitalisation of China's financial system; the program of "India Stack" or the Digital Financial Services (DFS) provided by the Bank of Ghana award winner in 2024 (AFI, 2024; Fazal & Ahmed, 2023).

AI significantly enhances financial inclusion by addressing various barriers and improving access to financial services for underserved populations. AI applications can provide scoring methods to ensure low-income earners, the poor, women, youths and small businesses participate in the mainstream financial market. Also, AI adoption can improve risk detection, management and measurement, address the problem of information asymmetry, avail customer support and helpdesk through chatbots, fraud detection, and cyber security (Mhlanga, 2020; Yanting & Ali, 2023).

Therefore, AI applications, such as improving customer experience and inclusion of individuals who would likely be excluded from the opportunity to obtain loans or other financial services, but for AI processing which is not biased by colour, race, gender, or religion, increased the financial inclusion (AFI, 2024). We observe that there is a complementary relationship between AI and financial inclusion. FI provides raw data on the state of provided financial services (FAS), so data are considered the fuel of artificial intelligence. Adopting the idea of inclusion of the excluded households ensures that all groups from the bottom of the pyramid will become financially active (Wang et al., 1984).

Many studies investigate the relationship between financial inclusion and AI. Dakalbab et al. (2024) conducted a systematic literature review of AI techniques in financial trading. They reviewed 143 research articles published between 2015 and 2023. Papers implemented AI techniques in the financial trading market. Researchers observed eight financial markets that used AI predictive models, and they found that technical analysis is more adopted than fundamental analysis. Findings show that 16% of the selected research articles entirely automate the trading process; they also identified 40 different AI techniques used as standalone and hybrid models. Other academics have already developed several machine-learning models.

Adeoye et al. (2024) explored AI and data analytics initiatives for financial inclusion; they yielded several insights obtained from successful projects such as M-Pesa, Jumo and Tala. They found a pressing need for continued efforts to build inclusive financial systems in developing economies such as African countries.

Challenges and Prospects

Financial inclusion data reveals world gaps disclosed by the financial access survey. Although more than 80% of adults had access to bank accounts, with the gender gap narrowing from 14.1% in 2019 to 9.4% in January 2024, also the percentage of adults making or receiving digital payments other than mobile money rose from 19.3% to 45.4% (AFI, 2024).

Studies investigated the impact of financial innovation on traditional banks. Liao and Chung (2024), Mhlanga (2020), Oualid et al. (2022), and Pattnaik et al. (2024) have discussed the impact of Fintech as an algorithmic trading model on investment efficiency and risks. They analysed the effect of RegTech, governance, and shadow banking on financial inclusion (Bao & Huang, 2021).

Other researchers explore the role of AI and ML in the (BFSI) sector, enhancing service quality and trust and mitigating risks. Gatzert and Schubert (2022) and Oualid et al. (2022) obtained findings from investigating chatbots, robo-advisors, sentiment analysis, and text mining that expand insights into customer behaviour. Moreover, scholars devoted attention to the challenges of cybersecurity and data protection in the (BFSI) industry and the role of early warning systems (EWS) in risk mitigation (Gatzert & Schubert, 2022).

Subramaniam et al. (2024) used panel data from 29 countries categorised from high to low in the AI Index developed by Stanford University from 2017 to 2021 to measure the impact of artificial intelligence on financial inclusion. They developed two empirical models for proxied financial inclusion; the first is based on the demand side, and the second is proxied on the supply side. Other variables are added, such as education, income, and rural populations. Institutional quality indicators are integrated to represent the infrastructure-sided factors.

Researchers and other previous studies use the AI Index developed by Stanford University for the first time as a variable measuring AI adoption. Using panel data and the dynamic GMM method, they found a significant positive impact between AI and financial inclusion.

To measure the effects of AI on financial inclusion, researchers commonly employ a variety of methodologies, as shown in the table above. Regression models are frequently used to explore the relationship between variables; qualitative methods are used to analyse complex relationships between variables to provide empirical evidence and highlight the significance of AI in achieving financial inclusion (see Table 1). This includes bibliometric analysis (Dakalbab et al., 2024; Pattnaik et al., 2024).

Table 1

Methodologies and Variables Measuring the Impact of AI on Financial Inclusion

Authors	Methods	Variables	Results
Yang and Masron (2024)	They investigated the relationship between digital transformation and financial inclusion on credit risk. Employing the Generalized Method of Moments (GMM) and data from 116 Chinese banks from 2014 to 202.	Credit risk; Digital Transformation Index; Digital Financial Inclusion Index; Bank Size	The results show that digital transformation significantly and dynamically reduces bank credit risks, and inclusive finance plays an interactive role. As financial inclusion increases, this risk-reducing effect will increase.
Subramaniam et al. (2024)	They explore the impact of artificial intelligence on financial inclusion using panel data from 29 countries from 2017 to 2021. They used the Panel-GMM estimations	Number of ATMs; Number of bank branches; Education; GDP per capita; Rural population; Inflation; Government expenditure; Internet access; Artificial Intelligence Index; Institutional Quality Index	The findings show that artificial intelligence is a statistically significant determinant of financial inclusion and helps promote financial inclusion in countries that adopt artificial intelligence
Triwibowo and Nurbasith (2023)	Using three dimensions: Access, Usage, and Quality. PCA method in Indonesia	Access: (Number of Bank Offices; ATMs) Usage: (Saving Account; Loan Account; Debit Card; Credit Card; Electronic Money; Transaction Volume; Quality: Real Interest Rate) Socioeconomic variables: (Gini ratio; Poverty rate; HDI)	Digital technology in the financial sector can enhance financial inclusion.
Li et al. (2022)	Testing the effect of ICT on financial inclusion based on data from worldwide countries in 2011, 2014, and 2017. Using linear regression models	Credit card users; Accounts of financial institutions; Number of ATMs; Debit Card users; Branches of commercial banks; Proportion of deposits to GDP; Number of depositors; Proportion of private credit to GDP; Number of borrowers	ICT level improves a country's financial inclusion by promoting the improvement and development of the digital payment system.

Ongo Nkoa and Song (2020)	Estimated the effects of institutional quality on financial inclusion in 51 African countries. Dynamic panel data using the GMM model are specified, covering the period of (2004-2018).	Composites financial inclusion index of the three indicators: (Number of active mobile phone accounts; number of bank branches; number of vending machines); (Education; GDP per capita; government expenditure; private investment; house consumption; number of telephone lines; institutional quality)	The findings suggest that institutional quality boosts financial inclusion and financial service penetration, accessibility, and use in Africa.
Camara and Tuesta (2018)	Measuring the FI index, using the demand and supply sides for 137 developed and less developed countries, using PCA.	Usage:(Account; Loan; Savings) Access:(ATMs) Barriers:(Distance; Affordability; Documentation; Lack of trust)	The degree of financial inclusion is determined by three dimensions: usage, barriers and access to the financial system

Source: Collected by the researchers.

Despite the growing body of research on this topic, several gaps remain unaddressed. First, the reliance on secondary data and global reports limits the depth of empirical analysis, leaving room for more robust, field-based research. Second, while much has been written about the benefits and applications of AI in financial inclusion, little attention has been given to the methodological frameworks used to assess its impact, particularly concerning the AI Index. Third, the influence of institutional quality and regulatory frameworks on AI-driven financial inclusion remains insufficiently explored, especially in developing economies. Furthermore, most studies focus on macro-level indicators without adequately capturing the lived experiences of financially excluded populations at the micro level.

Addressing these gaps is crucial for developing a more nuanced understanding of AI's role in financial inclusion and ensuring its effective and equitable implementation.

Materials and Methods

The previous diverse methodologies ensure a robust analysis of AI's impact on financial inclusion, catering to different research needs and contexts. We conducted empirical research using a broad dataset spanning 7 years from 2017 to 2023. The dataset covers 35 countries ranked by levels of artificial intelligence development.

Econometric Model

Our empirical study investigates the impact of AI on financial inclusion, a multifaceted concept encompassing access to financial services, their usage and quality. The mathematical model was developed to quantify this impact and understand how AI could foster more inclusive financial systems, particularly in regions with limited financial infrastructure. To measure financial inclusion, we rely on three key factors that have been widely adopted in the literature. Access to financial services is measured by the number of ATMs per 100.000 individuals. ATMs are a critical infrastructure in determining how widely banking services are available to the population, particularly in areas where brick-and-mortar branches are scarce. The choice to measure access through the number of ATMs per 100.000 individuals stems from the central role that ATMs play in financial inclusion; they are a fundamental aspect of financial infrastructure, providing individuals with physical access to cash and facilitating basic banking transactions. ATMs offer a cost-effective and scalable way to extend banking services in regions with limited bank branches or poor transportation networks. To serve as a key indicator of financial access, especially in areas where digital banking services may not be as developed or accessible. The usage of financial products and services is captured by the volume of transactions and the penetration of e-money, proxied by the number of mobile accounts. This indicates how often individuals use financial products such as savings accounts, credit, or mobile payment systems. Quality is assessed through the institutional quality index, which reflects the regulatory and operational environment of the financial system, encompassing factors like trust, transparency and accessibility. The AI variable in our model is measured by the AI Vibrancy Tool developed by Stanford University (Maslej et al., 2024). Other factors are added to the empirical model, such as education, GDP per capita, government expenditure, number of mobile accounts, unemployment rate, and rural population.

Yang and Masron (2024) measured financial inclusion and transformation's role on bank risk. Using the Peking University Digital Financial Inclusion Index, they employed the GMM method and panel data from 116 Chinese banks from 2014 to 2021. Findings show that digital transformation significantly and dynamically reduces bank credit risks and financial inclusion.

Following Adeoye et al. (2024), Chinoda and Kwenda (2019), Harkut and Kasat (2019), Mhlanga (2020), Ongo Nkoa and Song (2020), and Subramaniam et al. (2024) who found that financial inclusion is due to micro and macro-economic variables and institutional variables. We specify a dynamic panel model as follows:

$$FI_{it} = \beta_0 + \beta_1 FI_{it-1} + \beta_2 AI_{it} + \beta_3 X_{it} + \mu_i + v_t + \varepsilon_{it} \quad (1)$$

Where $t = 1, \dots, T$, and $i = 1, \dots, N$, and $T$and N denote the time and the country, respectively. The dependent variable is which refers to the financial inclusion in the country i at time t.

The financial inclusion is measured by the number of ATMs per 100.000 inhabitants;

FI_{it-1} is a lagged variable that measures the memory effect of the financial inclusion process in a country i at $time_{t-1}$;

AI_{it} refers to the AI Index developed by Stanford University as a project of a 100-year study (AI100) based on nine chapters. We obtained the AI Index proposed by Stanford University, measured by the AI vibrancy index. We later used the aspects of the economic pillar (AI-ECO) and research and Development pillar (AI-R&D) for the robustness check. We chose those pillars to investigate, which contribute primarily to financial inclusion.

X_{it} is a vector of exogenous variables that include macroeconomic variables.

According to previous research, our empirical model is built as follows:

$$LnATMs_{it} = \beta_0 + \beta_1 LnATM_{it-1} + \beta_2 LnLnAI_{Index\,it} + \beta_3 LnEDU_{it} + \beta_4 LnGDP_{it} + \beta_5 LnGOV_{EXP\,it} + \\ + \beta_6 LnIQ_{it} + \beta_7 LnUNEMP_{it} + \beta_8 LnRPOP_{it} + \beta_9 LnMob\_Acc_{it} + \mu_i + v_t + \varepsilon_{it} \quad (2)$$

$LnATM$ is the dependent variable, the logarithm of the number of automated machines per 100.000 inhabitants, proxied the financial inclusion.

$LnEDU$ refer to education levels, which generally positively affect financial inclusion (Fengju & Wubishet, 2024; Ongo Nkoa & Song, 2020). Also, combining AI tools, such as machine learning, with financial education can allow the unbanked to access financial services, so education provides the capacity and skills to use financial instruments. AI tools can help people make financial decisions and strengthen creditworthiness.

$LnGDP$ refers to the logarithm of the gross domestic product per capita, which describes the market size and countries' domestic production. Levels of GDP per capita contribute more to the elasticity of other economic factors and thus reduce the digital divide. It may reflect the ability to access the internet and technical devices, thus controlling digital technologies to expand financial inclusion (Fengju & Wubishet, 2024).

LnGov_Exp is public spending on education; it can be performed in the educational system.

$LnIQ$ redirect institutional quality variables. Theories of Patrick (1966) identified for the first time the relationship between financial development and institutional quality. It is a composite index developed by the World Bank. It contains scales from six variables (voice and accountability, political stability and absence of violence or terrorism, government effectiveness, regulatory quality, rule of law, and control of corruption. It provides insight into frameworks of the quality of institutions to empower financial inclusion.

$lnUNEMP$ represents the ratio of unemployed individuals to the total labour force. Countries with high unemployment may be excluded financially (Alabi & Olaoye, 2022); many findings show that unemployment affects financial inclusion negatively (Muriu, 2021).

$LnRPOP$ is the rural population variable; Wang and He (2020) noted that digital financial inclusion is different from traditional financial inclusion, that's means providing access to financial inclusion services (FAS) through digitalisation. Digital financial inclusion services reduce transaction costs in rural areas due to lower marginal costs. Besides AI being used as a relationship broker, banks have introduced chatbots to allow vulnerable households in rural areas to access financial advice and assistance that they cannot get when dealing with humans, especially those who fear judgments on their appearance or the nature of their work (Mhlanga, 2020).

$lnMob_Acc$represented the number of mobile accounts. The increase in mobile accounts is one factor that drives the excluded population to adopt and expand technology and use the Internet. Countries like China, Canada, the United Kingdom, and the United States have almost 100% internet coverage. Several prerequisites can slow the obtaining/ access/ usage of line numbers in many developing countries with low income and literacy (Alabi & Olaoye, 2022).

Accumulation theory refers to the concept that periods of economic growth are contingent on the emergence of certain institutions that facilitate capital accumulation. Still, these institutions become obstacles to growth continuity over time, leading to recessions and economic crises. Therefore, they must be replaced by new institutions that promote accumulation (Harcourt, 2001). Because economic variables are dynamic, introducing AI into the financial inclusion model would delay the marginal substitution process by specific periods. On the other hand, creating a lagged independent variable that can measure the memory of the potential effects on financial inclusion is necessary.

We used unbalanced panel data for 35 countries from 2017 to 2023. The data from last year are available, so we proceeded with the two-stage-least-squares (TSLS) and Generalized Methods of Moments (GMM) estimator because it provides accuracy in prediction, considering variance in time. The TSLS technique was designed by Cumby et al. (1983) and is considered an improved version of the OLS approach, which fails to consider the unobserved heterogeneous impacts or the possible link between the regressors and the error term. Ignoring these issues may result in biased estimates. Thus, the TSLS technique uses an instrumental variable approach (IV), which is preferred over the simple OLS technique. This is one of the best estimators for correcting the endogeneity issue. The procedure used in the TSLS involves the replacement of an endogenous variable with a proxy-independent variable, which helps to overcome the issue of endogeneity and provides correct estimates. In addition to the TSLS technique, GMM is another instrumental variable technique used in our analysis. According to Arellano and Bond (1991), the GMM-estimator optimises all the linear moment restrictions optimally and extends to cover the case of our unbalanced panel data. Due to difficulties in selecting IV, Arellano and Bond (1991) solved this problem by applying the GMM technique by including lags in regressors.

Data Sources

We used panel data covering 35 countries over the period 2017 to 2023. Chosen countries are classified, including the Global AI Index, into three levels from high, medium and low AI adoption constituted from nine chapters which are as follows: (1) Research and Development; (2) Technical Performance; (3) Responsible AI; (4) Economy; (5) Science and Medicine; (6); Education; (7) Policy and Governance; (8) Diversity; (9) Public Opinion (Maslej et al., 2024). Table 2 shows the concerned countries.

Table 2

AI Index Ranking Countries

High AI (17.06-15.06)	Up Medium AI (14.84-14.02)	Low Medium (13.88-11.13)	Low AI (9.96-3.71)
United States	Norway	Poland	Estonia
China	Portugal	Sweden	Mexico
United Kingdom	Finland	Malaysia	Brazil
India	Switzerland	Saudi Arabia	New Zealand
United Emirates	Italy	Australia	South Africa
France	Austria	Russia	
South Korea		Ireland	
Germany		Turkey	
Japan			
Singapore			
Spain			
Luxembourg			
Belgium			
Canada			
Netherlands			
Denmark			

We employ data between 2017 and 2023, which is dictated by the availability of data on artificial intelligence. Data on dependent and independent variables are collected from many sources, such as the World Bank database (DataBak, n.d.), World Governance Indicators,[1] and Stanford University through the AI Vibrancy Tool.

The financial inclusion variable was proxied by the number of Automated Teller Machines (ATMs) per 100.000 adults, which is collected from the Financial Inclusion Survey (FAS) generated by the World Bank (DataBak, n.d.). Our primary variable of interest is the Global AI Index measured by the AI Vibrancy Tool provided by Stanford University, which indicates the readiness of AI adoption and AI development in 35 countries. We also used the economic pillar (AI_ECO) and the (AI_RD) from the aspects of the research and development pillar. Going toward the instrumental variables, we relied on evidence from economic theory and empirical studies; macro-economic variables were introduced as education (EDU) measured by the percentage of school enrollment secondary to total education rate;(GDP) is the gross domestic product per capita constant 2010 US$; (GOV_EXP) is the government expenditure on education as per cent from total expenditure (UNEMP) is the unemployment rate as per cent; (RURAL_POP) is the rate of rural population from total; (Mob_ACC) is the number of individuals owning mobile number. These variables are collected from the World Bank database. ; (IQ) refers to the institutional quality measured by six indicators provided by (the WGI dataset) including (rules of law, control of corruption, regulatory quality, political stability, voice and accountability, and government effectiveness).

[1] https://www.worldbank.org/en/publication/worldwide-governance-indicators

Results

Before moving to the econometric test estimation, we first presented the descriptive statistics of all the variables. In this study, we have used variables and indexes to measure the impact of artificial intelligence on financial inclusion. Descriptive statistics of all the explanatory variables are shown in Table 3 to provide a detailed review of the variables. We observe that most variables' mean and median scores are pretty close. The mean of variables is for LTMs (4.41); LEDU (4.21); LIQ (4.27); LAI_DX (2.55); LAI_EC (1.00): LAI_RD (0.21); LGOV_EXP (2.43); LUNEMP (1.70); LGDP (11.42); LMOB_ACC (17.37) and LRURAL_POP (11.36). Variables are relatively symmetrical distributed.

Positive Skewness is observed for LGDP (2.12) and LUNEMP (1.04), which indicate a rightward tail where higher values dominate. Theoretically, this is true when a small percentage of individuals have higher incomes or in the case of hyperinflation in some countries due to economic and political crises. Also, negative Skewness is observed for LEDU (-1.37) and LIQ (-1.38). In countries with strong educational systems, most individuals complete their secondary education, so there is a low value for individuals who do not. However, those countries have relatively strong government institutions across most sectors, while a few institutions experience weak performance due to exceptional issues. This creates a leftward tail in the data.

The variable (LATMS) shows relatively low variability and positive skewness, indicating gradual but consistent improvements in financial inclusion. The role of Institutional Quality (IQ) appears skewed and concentrated at lower values, highlighting potential institutional challenges. LRURAL_POP has significant variability and non-normal behaviour, suggesting rural financial inclusion remains inconsistent and is influenced by extreme deviation (7.11).

Table 3

Descriptive Statistics

Variable	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera Prob.
LATMS	4.42	4.40	6.16	3.03	0.675	0.36	2.97	0.0719
LAI_DX	2.55	2.63	4.29	0.57	0.638	0.12	3.92	0.0097
LAI_EC	1.00	1.02	2.82	-0.87	0.559	0.59	4.87	0.0000
LAI_RD	0.21	0.36	3.26	-4.61	1.296	-0.31	4.33	0.0000
LEDU	4.21	4.33	4.56	3.06	0.309	-1.37	3.89	0.0000
LGDP	11.42	11.04	17.47	9.75	1.543	2.12	8.06	0.0000
LGOV_EXP	2.43	2.42	3.07	1.48	0.283	-0.50	3.96	0.0001
LIQ	4.27	4.43	4.59	2.80	0.355	-1.38	4.10	0.0000
LMOB_ACC	17.37	17.54	21.32	13.58	1.655	0.18	2.93	0.5124
LRURAL_POP	14.36	15.76	20.63	-25.33	7.11	-4.97	28.12	0.0000
LUNEMP	1.70	1.62	3.36	0.80	0.495	1.04	4.31	0.0000

Source: Eviews 13 outputs.

Table 4

Correlation Matrix

	LATMS	LAI_DX	LEDU	LGDP	LGOV_EXP	LIQ	LMOB_ACC	LRURAL_POP	LUNEMP
LATMS	1								
LAI_DX	0.2867	1							
LEDU	0.0658	0.0255	1						
LGDP	0.0726	0.1101	0.2221	1					
LGOV_EXP	-0.3391	-0.1744	-0.0839	-0.3851	1				
LIQ	-0.0893	0.0672	0.6091	0.0220	-0.0191	1			
LMOB_ACC	0.3203	0.4080	-0.4846	0.0988	-0.1097	-0.6341	1		

LRURAL_POP	0.1743	0.0460	-0.1993	0.0070	-0.0944	-0.2746	0.3943	1	
LUNEMP	-0.04914	-0.3265	-0.3490	-0.4015	0.0827	-0.2341	0.0649	0.1547	1

Source: Eviews 13 outputs.

We observe positive correlations between variables as shown in the Table 4. Coefficients of (LTMs - LAI_DX) are (0.29); (LATMs-LMOB_ACC) (0.32); (LATMs-LRURAL_POP) (0.17) which mean that AI adoption, mobile account access, moderately contributes to financial inclusion. Surprisingly, the rural population shows a positive correlation, possibly due to the role of mobile solutions in rural inclusion.

A negative correlation also is between (ATMs-LGOV_EXP) (-0.34), which means that higher government spending might not directly enhance financial inclusion. Also, we observed positive correlations between (LAI_DX-LMOB_ACC) (0.41), referring to a strong positive correlation and the AI's role in enhancing financial inclusion due to the positive role of mobile technology in AI adoption.

Negative correlations between (LAI_DX-LUNEMP) (-0.33) suggest that AI adoption reduces unemployment. Other positive correlations are observed, such as (LEDU-LIQ) (0.61), (LEDU-LGDP) (0.22), and (LMOB_ACC-LRURAL_POP) (0.39).

The unemployment variable shows a negative correlation with most variables such LATMs (-0.05); LAI_DX (-0.33); LEDU (-0.35): LGDP (-0.40); LIQ (-0.2) indicates unemployment impairs inclusion, education and economic growth and unemployed populations have limited access to formal institutions.

TSLS and GMM Estimation

The estimation is performed using TSLS and GMM estimators. The estimators exploit all the linear moment restrictions that follow from particular specifications to cover the case of unbalanced panel data. The study focused on models with predetermined but not strictly exogenous explanatory variables in which identification results from a lack of serial correlation in the errors.

Table 5

TSLS & system-GMM Estimation

Variables	**TSLS Model**	**Sys-GMM Model 1**	**Variables**	**Sys-GMM Model 2**
LATMS(-1)		0.5445** (0.4876)	**LATMS(-1)**	0.7770* (0.4659)
LAI_DX	0.2519** (0.1105)	0.2182** (0.0983)	**LAI_EC**	0.4037*** (0.0983)
			LAI_RD	0.0935* (0.0501)
LEDU	0.6412*** (0.0882)	0.6271*** (0.1795)	**LEDU**	0.5895*** (0.1699)
LGDP	-0.0602*** (0.0082)	-0.060* (0.0316)	**LGDP**	-0.0573* (0.00297)
LGOV_EXP	-0.7531*** (0.0596)	-0.7458*** (0.1587)	**LGOV_EXP**	-0.8050*** (0.1486)
LIQ	-0.1636 (0.1139)	-0.1333 (0.4608)	**LIQ**	-0.3098* (0.1709)
LMOB_ACC	0.1124*** (0.0275)	0.1188*** (0.04324)	**LMOB_ACC**	0.0415 (0.0473)
LRURAL_POP	0.0060*** (0.0015)	0.0056* (0.00627)	**LRURAL_POP**	0.0080 (0.0059)
LUNEMP	0.0674 (0.0556)	0.0550 (0.1009)	**LUNEMP**	0.1092 (0.0936)

Constant	2.0992*** (0.5852)	2.0260*** (1.5081)	**Constant**	4.3797** (1.6156)
Observations	209		Observations	209
Number of countries	35		Number of countries	35
R^2	0.3097		AR (2) test	0.3439
F-test	9.9240***		Hansen test	0.7970
Hansen test (p-value)	0.6782			
AR (2) (p-value)	0.2666			

Note. $*\,p < 0.1$; $**\,p < 0.05$; $***\,p < 0.01$; standard deviations robust to heteroskedasticity in parentheses.

Source: Eviews 13 outputs.

Theory supports financial inclusion as driver of development by reducing imperfections, promoting savings and facilitating capital accumulation. Artificial intelligence accelerates the process. Dynamic panel results show that estimated results from using TSLS and sys-GMM are positive. Statistically significant memory effects from financial inclusion presented by the number of ATMS in previous years were presented from GMM estimation (Chinoda & Kwenda, 2019; Subramaniam et al., 2024).

As shown in Table 5, the estimated model from TLST employing ATMs proxied to financial inclusion suggests that AI plays a vital role in boosting FI. Specific FI increases by 1%; it causes upward movements in (LAI_DX) by 0.2519%; (LEDU) by 0.6412%; (LMOB_ACC) by 0.1124; (RURAL_POP) by 0.006%. Negative coefficients such as (LGDP) by -0.0602% and (LGOV_EXP) by -0.7531% are statically significant due to the lack of government measurements to adopt AI (Adeoye et al., 2024). More explanations are elaborated in Sys-GMM. Table 5 also reports some necessary diagnostic tests for the validity of TSLS estimation. These tests include R^2 and the F-test. R^2 is a measure of goodness of fit, and the (p-value) is more significant than 0.5; this highlights that the regressors explain more than 50% of the variations in the outcome variable in the TSLS model. The value of the F-test is significant, suggesting the joint significance of the variables.

Findings suggest that increased financial inclusion might not affect GDP and government expenditure positively. The key negative coefficient observed between government expenditure and inclusion, specifically in the impact of ATMs and government expenditure (LGOV_EXP) with a coefficient of -0.7531, challenges the assumption that higher government spending directly enhances access to financial services. Our findings support the idea that GDP and government expenditure, while necessary for economic development, do not necessarily foster financial inclusion directly or significantly. Similarly, GDP often used to measure a nation's overall economic performance, fails to show a straightforward positive impact with financial inclusion in our analysis. While a growing economy can lead to more financial opportunities, it does not guarantee that those opportunities reach all population segments. The study points to the critical role of technology, particularly AI and mobile solutions, in driving inclusion, especially in rural and underserved populations. These findings emphasise the need for targeted policies that prioritise technological innovations and ensure that the benefits of economic growth are distributed more equitably across all segments of society.

Robustness Check

For the GMM model, the outcomes of the robustness test and the substitution of independent variables results are represented in Table 5. For this analysis, we are using (AI_ECO) and (AI_RD) as a substitute for the original independent variable (AI_DX). The GMM model has been re-estimated using the instrumental variables method, and the resulting outcomes can be for robustness check results. Upon analysing outcomes, it becomes evident that artificial intelligence levels play a crucial role in promoting the expansion of financial inclusion. The findings show that LATMs(-1) have a significant coefficient (0.5445) at 0.005 level using the first GMM model, including the global artificial intelligence index (AI_DX). The second model for the robustness check coefficient also has a significant value (0.777) at 1%, which means high precision warrants further robustness checks; financial inclusion has a positive and statistically significant memory effect on its current level (Chinoda & Kwenda, 2019).

(LAI_DX) the global index of artificial intelligence is significant at ($p<0.05$), which means that the increase in AI applications leads to financial inclusion by 0.2182%. For the second model, the coefficients of both pillars, economics and research and development, are significant at 1% and 10%, respectively. That means the integration of artificial intelligence in the economy (0.403) and increasing research and development investments (0.093) lead to financial inclusion. This supports the role of artificial intelligence in improving accessibility, efficiency and cost-effectiveness of financial services, particularly through Fintech innovations. The significance at the 10% level of the research and development pillar by (0.093) highlights the early-stage benefits of research and development investments in AI.

Education drives development, so we notice through results that the variable (LEDU) has high significance in both models; coefficients refer to education strongly promoting financial inclusion, respectively (0.6271) and (0.5895). This correlates education levels with improved digital literacy, highest financial knowledge and the ability to access and use AI-driven financial services. Results are consistent with an economic theory linking human capital development to technological adoption.

Contrary to economic theory, growth hurts financial inclusion; this may indicate that high incomes are concentrated in affluent urban populations, exacerbating rural financial inclusion (Adel, 2024; Ongo Nkoa & Song, 2020; Mejía & Gil, 2019). Also, the inequalities in GDP distribution led to marginalised groups in the financial system and financial exclusion.

Also, government expenditure has an adverse effect (Ongo Nkoa & Song, 2020). This counterintuitive result may come from inefficient allocation of public resources, corruption or expanding priorities that do not target financial infrastructure directly. Governments must endorse necessary government measures.

Also, institutional quality has a weak and negative effect; this may suggest a failure of government measurement and AI readiness due to the early stage of AI adoption, particularly the governance index, which may not be the appropriate measure of AI readiness. We suggest the Government AI Readiness index in the subsequent research.

The mobile account access variable has a significant coefficient in the first model at 1% but is not significant in the second model. (LMOB_ACC) enhances financial inclusion by (0.1188) supporting the importance of mobile banking infrastructure in increasing financial access. Hence, the non-significance in the second model is possibly due to collinearity with artificial intelligence adoption.

Rural population and unemployment are statistically insignificant in both models. Rural population size alone does not affect financial inclusion unless coupled with targeted interventions like AI-enabled rural banking services. Unemployment levels may not directly drive financial participation without financial literacy and access.

Discussion

Financial inclusion has primarily focused on economic factors, emphasising demand and supply side determinants. The literature review highlights the significant role of artificial intelligence in transforming financial inclusion by overcoming traditional barriers and expanding access to underserved populations. AI applications in credit scoring, risk management, and fraud detection offer innovative solutions, enabling equitable access to financial services for low-income earners, women, and small businesses. Empirical evidence underscores the complementary relationship between AI and financial inclusion, as AI leverages raw data to enhance financial services accessibility and inclusion for excluded groups. Despite these advancements, challenges remain, including data quality issues and the ethical concerns of AI implementation, particularly in developing economies.

Utilising our theoretical analysis and examining unbalanced panel data from 35 countries from 2017 to 2023, this study employed TSLS and GMM techniques. We investigated the impact of artificial intelligence adoption on financial inclusion in 35 countries most developed in AI ranking. We mobilised the ATMs per 100.000 inhabitants as a theoretical framework, which proxied financial inclusion. The econometric model we employed is the TLST and GMM system, which addresses the endogeneity problems proper to such dynamic models by using instrumental variables. We ensured the robustness of our results by conducting various diagnostic tests, including multicollinearity and instrument validity.

An empirical study employing TSLS and System GMM estimators demonstrates statistically significant memory effects of financial inclusion, as indicated by the number of ATMs from prior years. These findings align with prior literature confirming that financial inclusion exhibits a positive and persistent impact over time (Chinoda & Kwenda, 2019; Subramaniam et al., 2024). The coefficient of lagged ATMs is significant at the 5% level, underscoring the self-reinforcing nature of financial inclusion. The analysis reveals that AI has a significant and positive role in fostering financial inclusion. The global artificial intelligence index (LAI_DX) significantly drives financial inclusion, with a 1% increase in AI applications leading to a 0.2182% improvement. Substituting AI variables (AI_ECO); (AI_RD) confirms robustness, showing significant impacts of AI economic pillar (0.403) and research and development (0.093) at the 1% and 10% levels, respectively. These findings emphasise the critical role of AI investments in enhancing financial services and highlight the early-stage benefits of AI-driven research and development initiatives.

Education (LEDU) emerges as a pivotal driver of financial inclusion, with consistently high significance across models. The coefficients (0.6271 and 0.5895) illustrate a strong positive correlation between education and financial inclusion, aligning with economic theory that links human capital development to technological adoption. Higher education levels correlate with improved digital literacy and financial knowledge, enabling better access to AI-enabled financial services.

However, results were observed for economic growth (LGDP) and government expenditure (LGOV_EXP); both variables exhibit significant adverse effects on financial inclusion, suggesting structural issues. High-income concentration in affluent urban areas and unequal GDP distribution may exacerbate financial exclusion in rural areas, as suggested by prior studies (Adel, 2024; Ongo Nkoa & Song, 2020; Tinta et al., 2022). Similarly, inefficient spending of public resources, corruption, and misplaced spending priorities could explain the negative impact of government expenditure. This highlights the need for targeted public investments and institutional reforms to address financial infrastructure and rural inclusion.

Institutional quality (LIQ) shows a weak and negative effect, potentially due to the early stage of AI adoption and the inadequacy of governance indices as measures of AI readiness (Ali et al., 2016; Hankins et al., 2023). Future research should consider alternative metrics, such as the Government AI Readiness Index, to better capture institutional readiness for AI-driven financial transformation. Mobile account access (LMOB_ACC) demonstrates significant positive effects in the first model (0.1188) but becomes insignificant in the second robustness check model, possibly due to collinearity with AI variables. This finding underscores the importance of mobile banking infrastructure in driving financial inclusion, although its significance may depend on broader technological adoption.

Finally, rural population and unemployment are statistically insignificant in both models, suggesting that these factors alone do not directly influence financial inclusion. Instead, targeted interventions such as AI-enabled rural banking services and financial literacy programs are necessary to make an impact.

The results of this study provide robust evidence supporting the theoretical frameworks. Financial inclusion is a key development driver that reduces market imperfections, promotes savings, and facilitates capital accumulation. The role of artificial intelligence as an accelerator of financial inclusion is evident through its capacity to enhance the accessibility, efficiency, and cost-effectiveness of financial services.

While this study provides robust empirical evidence on the role of artificial intelligence (AI) in advancing financial inclusion, it is important to acknowledge several limitations. First, relying on ATM data as a proxy for financial inclusion may not fully capture the diverse and evolving dimensions of financial services access, especially in regions where mobile payments and alternative digital finance models are gaining prominence. The study focused on 35 countries, while helpful in examining the most developed nations in AI adoption, limiting the findings' generalizability to developing economies where AI adoption may be at earlier stages. Future research could incorporate more pertinent financial inclusion measures, such as digital services usage or access to mobile money, to capture a broader view of financial inclusion dynamics. Moreover, ethical concerns and data quality issues related to AI implementation, particularly in low-income or developing economies, require further attention. The evolving nature of AI technologies and their impacts on financial systems necessitate ongoing investigations into long-term effects. Lastly, the institutional quality variable's weak and negative effect suggests that governance indices may not adequately reflect the readiness for AI adoption. This warrants future research to explore more relevant measures of institutional preparedness for AI-driven financial transformation.

Conclusion

This study underscores the vital role of AI in shaping the future of financial inclusion. The empirical evidence demonstrates that AI adoption enhances financial accessibility by overcoming traditional constraints, optimising risk assessment, and fostering innovation in financial services. Artificial intelligence is still in its early stages, and some countries remain cautious about employing specific applications, such as (ML) technologies. Government measurements stem from the need to develop alternative indicators capable of keeping pace with this significant advancement, such as the digital financial inclusion index or the intelligent financial inclusion index. These indicators could encompass the profound changes that have become central to the standards of the financial and banking industries. Therefore, supporting and advancing research across various sectors is imperative to pave the way for the metaverse era.

In conclusion, while AI is still nascent, its potential to reshape the financial landscape cannot be overstated. This study emphasises the urgent need for continued research, investment in AI technologies, and policy reforms to ensure that the benefits of financial inclusion are equitably distributed. As AI continues to evolve, it will undoubtedly play an increasingly pivotal role in shaping the future of financial services, driving greater accessibility, efficiency, and innovation. AI’s 0.2182% effect on financial inclusion highlights the substantial potential of AI to enhance financial access, emphasising the technology’s role in overcoming barriers to financial services. The consistently significant relationship between education and financial inclusion (coefficients of 0.6271 and 0.5895) reinforces the connection between human capital development and successful AI adoption. The increase of 1% in AI applications results in a 0.40% and 0.09% improvement in financial inclusion, underscoring the significant impact of economic and R&D investments in AI. Despite the promising results, challenges related to institutional quality, mobile account access, and government expenditure highlight the need for targeted interventions to improve financial systems and promote rural inclusion.

These findings collectively suggest that while AI has made significant strides in enhancing financial inclusion, continued research and institutional reforms are critical to ensuring equitable access to financial services across all sectors of society.

Policy Implications

The rapid adoption of artificial intelligence (AI) in financial systems presents both opportunities and challenges for financial inclusion :

AI Integration: Policymakers should prioritise AI adoption in financial systems, focusing on economic integration and research and development investments to expand financial inclusion.

Education: Investments in education and digital literacy are essential to ensure broader access to AI-enabled financial services.

Regulatory and ethical measures must developed, and responsible AI deployment and consumer protection challenges are essential for sustainable financial inclusion.

Targeted Public Spending: Governments need to reallocate resources toward improving financial infrastructure and addressing disparities in GDP distribution.

Institutional Reforms: Institutional frameworks should be strengthened to support AI readiness, with better governance measures tailored to early-stage AI adoption.

Rural Interventions: Specific initiatives, such as AI-driven rural banking and mobile financial solutions, must overcome barriers in underserved areas.

Suggestions for Future Research

Future research should explore additional dimensions of AI-driven financial inclusion, particularly focusing on alternative AI metrics by investigating more comprehensive AI indices, such as the Digital Financial Inclusion Index or the Intelligent Financial Inclusion Index, to better assess the evolving role of AI in financial accessibility.

Ethical and Regulatory Challenges by examining the ethical implications of AI adoption in financial services, including algorithmic bias, data privacy concerns, and the role of regulatory frameworks in ensuring fair AI deployment. Also, sectoral analyses will determine how AI-driven financial inclusion impacts specific industries, such as microfinance, insurance, and digital lending platforms—also analysing long-term trends in AI adoption and financial inclusion, considering how AI innovations evolve and their sustained impact on financial accessibility over time.

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Conflict of Interest

The authors confirm that they have no financial or personal relationships that could have influenced the findings of this study.

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