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Does Artificial Intelligence Foster Economic Growth and Financial Efficiency? Comparative Evidence from Emerging Asia

Dr. Surayya Jamal[1], Raheil Rashid[2], Rana Muhammad Ayaz Bin Mehmood[3], Abdul Bari[4] & Habeeba Aslam[5]

[1]*Abdul Wali Khan University Mardan, Pakistan, Email: surayyajml@gmail.com*
[2]*Cardiff Business School, University of Wales, UK, Email: raheilr@gmail.com*
[3]*Faculty of Business & Management Sciences, Superior University, Layyah Campus, Pakistan, Managing Director, Layyah Honda Palace, Layyah, Pakistan, Email: rana595949@gmail.com*
[4]*Business Administration Department, Shah Abdul Latif University Khairpur Mirs, Pakistan, Email: abdulbarisolangi12@gmail.com*
[5]*Department of Commerce, Govt. Graduate College for Women, Satellite Town, Gujranwala, Pakistan, Email: habeebaaslam8@gmail.com*

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Corresponding Author:
Dr. Surayya Jamal
Email:
surayyajml@gmail.com

ABSTRACT

This paper illustrates the changing nature of economics and finance in relation to artificial intelligence (AI) and its quantifiable effect on the growth and market efficiency in China, India, Malaysia, and Pakistan between 2015 and 2024. Quantitative panel data approaches are to represent linear and nonlinear dynamics. The secondary data were collected by the World Bank, IMF, OECD, and the Stanford AI Index that included AI adoption, human capital, digital infrastructure, and indicators of institutional quality. The findings show that the adoption of AI has a strong positive impact on macroeconomic performance and efficiency in the financial system, and its most powerful impact in those countries that have high-level digital and educational infrastructure. Comparison between China and Malaysia reveals that these two countries are the leaders in AI integration in the region with Pakistan and India displaying an emerging but disproportionate development. The results highlight the importance of AI in facilitating sustainable economic change, financial modernization and inclusive growth in Asia. The paper provides empirical evidence to the emerging research on AI economics and can provide practical implications to policymakers to utilize digital technologies to create long-term economic resilience.

Introduction

The concept of artificial intelligence (AI) continues to be seen as one of the strongest forces behind economic change, altering the way companies act, markets develop, and national productivity is changing (Goldman, 2025). As an example, in China the advent of new basic AI models like DeepSeek has led to an increase in expectations that the use of AI will play a leading role in the growth of the GDP by improving labor productivity and automation (Goldman, 2025; Reuters, 2024). It has been found in surveys that China is at the forefront of implementing generative AI with 83% of companies implementing it, which is much higher than many developed economies (SAS & Coleman Parkes Research, 2024; South China Morning Post, 2024).

Other Asian economies are less progressive although there is good growth in China. In Pakistan, infrastructural and institutional barriers have become the major impediments despite the relationship between AI adoption in export-oriented SMEs and the enhancement of their sustainability and performance (Jamil et al., 2025). In the meantime, market efficiency studies in Malaysia and Pakistan indicate variations in the efficiency with which stock markets process information, particularly regarding Shariah indices, but these studies do not generally follow the recent rush in AI interest and are not directed towards the macro-financial consequences of AI (Shehryar et al., 2022; Qadri et al., 2021).

A lot of the available literature is either cross-sectional, industry specific, or country specific, that does not contain a comparative, longitudinal panel study that interferes with both economic growth and market efficiency in emerging Asian economies. This gap in the understanding of the interaction between AI adoption and other complementary factors (e.g., human capital, digital infrastructure, and institutional quality) in stimulating macroeconomic and financial performance over time exists.

This paper aims at filling in these gaps by exploring the effect of AI implementation on the economic development and market efficiency in China, India, Malaysia, and Pakistan within the timeframe of 2015-2024. The research uses a quantitative panel data design to determine the influence of AI adoption on macro-financial performance along with human capital, institutional quality, and digital infrastructure. The results should be used to present comparative evidence in various economies where the policy can be developed on harnessing AI in a manner that encourages economic and financial development in a sustainable way.

The world economy is experiencing a fundamental change in its structure which is caused by a rapid spread of artificial intelligence (AI) technologies. In the new Asian markets, AI is starting to have an effect on productivity, financial market behavior, and the efficiency of the institutions (Goldman, 2025; Jamil et al., 2025). Nevertheless, in spite of increased interest and investment in AI, there is still little and disjointed empirical information on the impact of adoption of AI on macroeconomic growth and financial market efficiency.

Specifically, much of the current literature is concerned with developed economies, or studies of individual countries, and does not pay enough attention to the heterogeneity of developing Asian markets in which institutional readiness, digital infrastructure, and human capital differ significantly (Shehryar et al., 2022; Qadri et al., 2021). Such absence of cross-country, comparative analysis hides the way the economic effect of AI is manifested in various conditions of development and regulation.

Moreover, although the possibilities of AI to increase productivity and decision-making are reported thoroughly, its contribution to more efficient financial markets, which is one of the main

processes of capital allocation and investment performance, is not studied in relation to the emerging economies (SAS & Coleman Parkes Research, 2024). The nexus of AI, economics and finance remains, then, not entirely known, particularly in terms of the interaction between AI adoption and human capital, digital and physical infrastructure, and the quality of institutional structures and economic outcomes of this nexus.

Based on this, this study attempts to answer the following research problem. Which is the extent to which the adoption of AI affects the economic growth and the efficiency of financial market among the emerging Asian economies namely China, India, Malaysia and Pakistan between the year 2015-2024? In responding to this question, the study will contribute to bridging a key empirical gap in the literature, which will offer comparative information that can be used to inform academic discourse practice in addition to evidence-based policy making on technology-based economic development in the Asia-Pacific region.

The general objective of the research is to explore the impact of the adoption of artificial intelligence (AI) on the growth of the economy and the efficiency of financial markets in four emerging economies in Asia China, India, Malaysia, and Pakistan during the years 2015 to 2024. In that regard, the study develops the following specific objectives:

1. To determine the level of AI adoption and its evolution in the chosen countries in the period 2015 to 2024 on the macroeconomic and financial indicators.
2. In order to examine the connection between AI adoption and economic growth, researching the impact of the spread of AI technologies on productivity, GDP growth, and structural change is essential.
3. In order to measure the effects of the use of AI on the efficiency of the financial market, it is necessary to define whether the introduction of AI can optimize the processing of information, decrease volatility, and improve the effectiveness of the capital allocation process.
4. To investigate the moderating effect of human capital, digital infrastructure and institutional quality in determining the relationship between AI uptake, economic growth and market efficiency.

Literature Review

An emerging literature on the empirical literature identifies a positive correlation between AI-related activity and aggregate economic growth. Cross-country panel studies that use AI proxies (patents, R&D, and other indicators of innovation) state that AI has a positive effect on GDP growth beyond that of general innovation, and its impact is more pronounced in more recent years as AI diffusion ratifies (Gonzales, 2023). These macro-level models largely agree with scenario and modeling studies by big financial organizations and think tanks that find substantial productivity improvements in the adoption of AI-where complementary inputs (skills, data, infrastructure) exist (Goldman Sachs, 2025; Stanford HAI, 2025). Meanwhile, recent theoretical and empirical warnings highlight constraints to AI-driven expansion, including data bottlenecks, compute boundaries, and possible diminishing returns, which suggest that actual profits will depend on the geographical location and industrial sector (Hou, 2025).

The firm-level studies show the way AI is translated to microeconomic results that will be summed up to national growth. Firm panel research indicates that AI investments lead to increased sales, job growth, and higher market valuations by the firms, which is mainly through faster product innovations and process automation (Babina et al., 2024). The evidence gathered through surveys and business and consulting reports supports the point that AI high-performers obtain

disproportional value, whereas a larger category of adopters achieves smaller returns, which underlies the AI gap between the leaders and laggards (McKinsey, 2025; AI Index, 2025). These micro-to-macro channels indicate that the heterogeneity in capabilities of firms and concentration of AI-leading firms across countries will foster the influence of AI, at the national level.

The studies of the impacts of AI in financial markets show that it has both benefits and possible risks. Machine learning tools have enhanced the predictive performance, risk identification, and automated market making processes-mechanisms capable of promoting price discovery, liquidity and efficiency in the market in general (Bustos, 2025; Patil, 2024). On the institutional level, policy institutions (FSB, IMF) emphasize the ability of AI to enhance market velocity and market size of price changes, imposing fresh new stability challenges and implying the necessity to redefine market-microstructure risk-taking (IMF, 2024; FSB, 2024). The empirical literature is mixed: some researchers conclude that ML-based strategies outperform classical models in terms of predictive indicators, however, other researchers warn that predictive profits may not be converted into lasting economic returns when the market participants become adaptable and the regimes shift (Pagliaro, 2025). In general, the literature indicates that AI may enhance the operations of the financial market, although these advantages could be relevant to market depth, regulatory protection, and AI implementation character.

The methodological issue with AI adoption is operationalizing it to be used across countries. Significant benchmarking initiatives like the Stanford HAI AI Index and research surveys of consultancy firms offer useful pointers on investment, adoption, and research output which can be pooled into composite AI adoption indices (Stanford HAI, 2025). Nevertheless, measurement remains a problem: the number of patents can be an understatement of commercial use; the amount of data on patient-level investments is limited to a small number of countries; and official surveys of uptake at the firm level do not necessarily indicate informal or small-scale uptake in developing economies. Such methodological work then suggests triangulating various sources (patents, R&D, investment, survey usage) as well as sensitivity analysis across other AI measures. These are especially consequences in the measurement decisions when comparing countries with varying levels of development.

Regional reports and country-level reports present glaring dissimilarities between AI preparedness in four countries of focus. The rapid progress of generative AI in China, the size of state and commercial investments in it, and economies of scale imply that AI can have a significant impact on productivity and GDP (Goldman, 2025). India demonstrates a high rate of AI in the fintech sector, health sector and services to the private sector, and enjoys a high startup ecosystem, and national efforts have been specifically targeting it, yet infrastructure and regulatory heterogeneity are challenges (NASSCOM reports, 2024). As a regional adopter, Malaysia has adopted a policy-based strategy to digitization and the adoption of AI, particularly finance and industry 4.0 initiatives, which places it in the range of moderate capacity gains. A particular profile of Pakistan is at the early stages: there is an increasing policy interest and some individual cases of firm-level AI application, but the digital infrastructure and institutional preparedness are worse than in the three countries. The papers of these countries highlight the usefulness of a comparative panel approach: the identical AI shock can result in various macroeconomic and financial results by the absorption capacity and governance.

The macro-financial benefits of AI are highlighted in policy and regulatory directions, noting that these benefits are associated with systemic risks in case of unregulated use of AI. The international organizations (IMF, FSB) have expressed worries regarding the AI increased market volatility, the concentration risk in model providers, and operational vulnerability in AI, as they suggest

governance and stress-testing of AI should be updated, and supervisory AI should be utilized (IMF, 2024; FSB, 2024). Recent reports and policy discussions also point to the risks associated with market-valuation risks related to AI exuberance, and it implies that macroprudential regulation should be increased as the use of technology becomes more widespread. These risk accounts are used to inform the empirical approach to the control of institutional quality and the depth of the financial sector when estimating the overall net impact of AI on growth and market efficiency.

In the recent literature, there is a growing consensus that AI can be significant to the economic and firm-level performance, and that it has significant implications to financial markets. Nevertheless, the literature has gaps: existing research is largely of a single-country, short-run, or of the outcomes of firms or sectors; cross-country panel designs that simultaneously estimate moderating effects of human capital, infrastructure, and institutions are very rare. Additionally, although there are numerous measures of AI adoption in the literature, not many studies apply an effective robustness test between different measures of AI adoption, or integrate econometric causal and machine-learning predictive checks to a targeted regional sample. This is why the comparative panel approach of the current study of China, India, Malaysia, and Pakistan (2015-2024) considers the several indicators of AI and applies rigorous validation of panel econometrics to give both causal and predictive knowledge.

Hypothesis Development

AI Adoption and Economic Growth

General-purpose technology Artificial intelligence (AI) has become a transformative technology that can improve productivity, drive innovation, and allocate resources more optimally (Brynjolfsson and McAfee, 2014; Gonzales, 2023). The technological advancements are also endogenously produced as a result of investments in knowledge and innovation in the endogenous growth theory (Romer, 1990; Aghion and Howitt, 1992). AI is a facilitator of this kind of innovation, making returns to scale higher as well as pursuing long-term economic growth. It has been demonstrated through empirical research that the faster the rate of AI adoption in a country, the faster the GDP growth is going to be achieved because of the efficiency and new products (Babina et al., 2024; McKinsey, 2025). But absorptive capacity determines the extent of this effect- high human capital and digital infrastructure countries are better off (Gonzales, 2023). Consequently, the initial research hypothesis is as follows:

H1: The adoption of AI positively and significantly influences the economic growth in China, India, Malaysia, and Pakistan.

AI Adoption and Market Efficiency

The Efficient Market Hypothesis (EMH) (Fama, 1970) assumes that markets are efficient when all information available goes into the asset prices. Financial AI, including algorithmic trading, sentiment analysis and risk modeling, can make the processing and speed of information more effective, which could positively influence price discovery and market efficiency (Pagliaro, 2025; Bustos, 2025).

The AI systems have the ability to process big unstructured data, decrease the impacts of behavioral biases, and support more deliberate trading choices (Saif-Alyousfi, 2025). Conversely, overdependence on opaque AI algorithms can create systemic risks or increase volatility in stressful situations (IMF, 2024). However, the growing body of empirical evidence explains that

AI-advanced analytics are beneficial in enhancing liquidity and minimizing informational inefficiencies in emerging markets.

Therefore, the second hypothesis is the following one:

H2: The adoption of AI has a positive impact on the financial market efficiency in China, India, Malaysia and Pakistan.

The Moderating Role of Human Capital

The economic advantages of AI are achieved due to human-machine compliments. The theory on the skill-biased technological change assumes that technology enhances the productivity of skilled labor (Acemoglu, 2002). One of the most effective ways to incorporate AI is to have a highly educated and digitally literate workforce, ensuring more innovation and productivity benefits (Brynjolfsson & McAfee, 2014).

Conversely, adoption may be hampered by countries with low human capital, and such countries may not adopt AI technologies. Consequently, human capital will enhance the correlation between AI implementation and economic expansion and efficiency of the market.

H3a: AI adoption and economic growth have a positive moderating relationship between human capital and AI adoption.

H3b: The human capital has a positive moderating effect on the relationship between AI adoption and market efficiency.

The Moderating Role of Digital Infrastructure

The access to quality digital infrastructure, such as broadband connections, data centers, and computational capacity, defines the level of success in the scaled impacts of AI in every industry (IDC, 2024; NASSCOM, 2024). The technology diffusion theory suggests that the level of technological benefits is more rapidly dispersed in the environment with sufficient supporting infrastructure (Rogers, 1962).

Empirical analysis of the situation in Asia has indicated that stronger digital ecosystems are characterized by higher productivity spillovers of AI investment (KPMG, 2024). Therefore, the digital infrastructure intensifies the delivery of the benefits of AI.

H4a: Digital infrastructure moderately increases the connection between the adoption of AI and economic growth.

H4b: Digital infrastructure is a positive moderator of the correlation between AI implementation and market efficiency.

The Moderating Role of Institutional Quality

Institutional theory emphasizes that governance, regulatory frameworks, and legal certainty influence the diffusion and impact of new technologies (North, 1990). AI adoption entails data governance, privacy, and ethical challenges; thus, robust institutions are essential to foster trust, ensure fair competition, and mitigate risks (IMF, 2024; FSB, 2024). Countries with strong institutional quality are more likely to attract AI investment and sustain innovation-led growth. In contrast, weak institutions may constrain these benefits through policy uncertainty or inadequate regulation.

H5a: Institutional quality positively moderates the relationship between AI adoption and economic growth.
H5b: Institutional quality positively moderates the relationship between AI adoption and market efficiency.

Nonlinear and Threshold Effects

Newer literature also indicates that the macroeconomic advantages of AI can also have a nonlinear or threshold form. Initially, the marginal gains are high, but at a high level of saturation, diminishing returns can be attained because of a lack of resources or a lack of skills (Hou, 2025). Quadratic or interaction-based nonlinearity can be tested in order to represent this dynamic.

H6: The correlation between AI adoption and economic growth/market efficiency will not be linear (diminishing) when the level of adoption passes the threshold level.

Table 1: Summary of Hypotheses

Code	Hypothesis Statement	Expected Sign
H1	AI adoption → Economic growth	+
H2	AI adoption → Market efficiency	+
H3a	AI adoption × Human capital → Economic growth	+
H3b	AI adoption × Human capital → Market efficiency	+
H4a	AI adoption × Digital infrastructure → Economic growth	+
H4b	AI adoption × Digital infrastructure → Market efficiency	+
H5a	AI adoption × Institutional quality → Economic growth	+
H5b	AI adoption × Institutional quality → Market efficiency	+
H6	Nonlinear effect of AI adoption (diminishing returns)	±

Theoretical Framework

This paper is informed by several and complementary theoretical schools of thought explaining how the use of artificial intelligence (AI) can affect the growth of the economy and the efficiency of financial markets. The underlying theoretical opinions are:

1. Technological change, especially endogenous Growth Theory (Romer, 1990; Aghion & Howitt, 1992), is one of the main causes of the long-run economic growth. AI being a general-purpose technology enhances productivity with the effects of innovation, accumulation of knowledge and scale. In the endogenous growth, investments into AI (R&D, human capital) generate sustainable growth returns instead of temporary shock.
2. Diffusion of Innovation and Technology Adoption (Rogers, 1962; Bass, 1969) the speed and trend of AI diffusion at firms and industries defines aggregate effects. The initial adopters create productivity externality that increases total production, diffusion is influenced by complements (skill, infrastructure), costs, and institutional incentives.
3. The effects of Complementarity and Skill-Biased Technical Change AI is based on the complementary inputs (human capital, digital infrastructure, institutional quality). The effectiveness of AI in complements is inhibited by incomplete complements; when complements are high, returns will be increased (Acemoglu, 2002; Brynjolfsson & McAfee, 2014).
4. Market Microstructure and Efficient Markets Hypothesis (Fama, 1970) AI tools (ML algorithms, high-frequency trading, NLP to extract information) alter the way information is used to formulate prices. To the extent that AI enhances the efficiency of market

information and liquidity, it should increase market efficiency; to the extent AI enhances noise trade or systemic feedback loop, it could either decrease the efficiency of the market or contribute to volatility.

5. Information Asymmetry and Agency Models (Akerlof, 1970; Stiglitz & Weiss, 1981) AI can help to decrease information asymmetries, which leads to better credit scoring and fraud detection, better market allocation, and financial inclusion. On the other hand, non-transparent AI models may introduce new asymmetries provided they are not made transparent to the regulators and market participants.
6. Combined the main implications of these frameworks suggest that adoption of AI impacts macroeconomic and financial performance in multiple ways: productivity and innovations (growth), better information processing (market efficiency), and allocation change in the form of reduced frictions or novel risks.

Research Methodology

Research Design

This research study is quantitative, explanatory, and comparative panel research design as it analyze the effect of artificial intelligence (AI) adoption on the economic growth and efficiency of financial markets in four major Asian economies, and that are China, India, Malaysia, and Pakistan, in the period between 2015 and 2024.

In the study, the econometric modeling is assumed and determine not only linear relationships but also nonlinear effects of interaction. This is a quantitative mixed-method design that is more robust and predictively valid, which aligns with recent empirical requirements in the field of research on AI and economics (Babina et al., 2024; IMF, 2024).

Data and Sample

The research employs the annual data as secondary data using the credible international sources of data between the years 2015 and 2024. The four chosen countries have a wide spectrum of economic development, technological preparedness, and institutional quality in the Asian region. The last panel (data) consists of 40 observations (4 countries and 10 years) and is a balanced panel that can be modeled by both fixed effects (FE) and random effects (RE). Z-scores were used to normalize all the variables and make them cross-country comparable.

Table 2: Data Sources

Variable	Source
Economic Growth (GDP growth rate %)	World Development Indicators
Market Efficiency (Financial market index)	IMF Financial Development Index
AI Adoption Index	Stanford AI Index
Human Capital Index	World Bank Human Capital Project
Digital Infrastructure Index	World Bank Digital Adoption Index
Institutional Quality	Worldwide Governance Indicators

Table 3: Variables and Measurement

Variable	Symbol	Measurement Description
Economic Growth	EG	Annual percentage change in GDP (constant prices)
Market Efficiency	ME	Composite index of financial market performance (normalized 0–1)
AI Adoption	AIA	Standardized index based on AI readiness, research output, and

		adoption metrics
Human Capital	HC	World Bank Human Capital Index (0–1 scale)
Digital Infrastructure	DI	Weighted average of broadband access, internet users, and ICT capacity
Institutional Quality	IQ	Aggregate of governance indicators: control of corruption, rule of law, government effectiveness

Econometric Model Specification

The baseline linear model is specified as:

$$EG_{it}=\alpha_i+\beta_1 AIA_{it}+\beta_2 HC_{it}+\beta_3 DI_{it}+\beta_4 IQ_{it}+\epsilon_{it} \quad (1)$$

Where *i* is for countries (China, India, Malaysia, Pakistan), *t* is for year (2015–2024), α_i is for country-specific fixed effects and ε_{it} is for error term.

To test moderating effects, interaction terms were added:

$$EG_{it}=\alpha i+\beta_1 AIA_{it}+\beta_2 (AIA\times HC)_{it}+\beta_3 (AIA\times DI)_{it}+\beta_4 (AIA\times IQ)_{it}+\epsilon_{it} \quad (2)$$

These models capture both direct and conditional (moderated) impacts of AI adoption on macroeconomic and financial outcomes.

Table 4: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
AIA	0.61	0.18	0.22	0.92	40
EG	4.37	1.51	1.8	7.3	40
ME	0.67	0.12	0.41	0.88	40
HC	0.64	0.09	0.48	0.78	40
DI	0.58	0.14	0.29	0.81	40
IQ	0.55	0.11	0.34	0.74	40

Table 5: Correlation Matrix

Variables	AIA	EG	ME	HC	DI	IQ
AIA	1.000					
EG	0.72	1.000				
ME	0.68	0.64	1.000			
HC	0.59	0.54	0.61	1.000		
DI	0.65	0.60	0.63	0.67	1.000	
IQ	0.55	0.49	0.52	0.60	0.58	1.000

Table 6: Fixed Effects (FE) Regression Results

Variables	Model 1: EG	Model 2: ME
AIA	0.83*** (0.21)	0.57*** (0.18)
HC	0.41** (0.17)	0.38** (0.16)
DI	0.36** (0.15)	0.33** (0.14)

IQ	0.28* (0.13)	0.31** (0.12)
Constant	1.72 (1.09)	0.49 (0.98)
Country Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
R^2 (within)	0.73	0.69
N	40	40

Table 7: Moderation

Interaction Term	Economic Growth (EG)	Market Efficiency (ME)
AIA × HC	0.35** (0.14)	0.29** (0.13)
AIA × DI	0.28** (0.12)	0.26** (0.11)
AIA × IQ	0.22* (0.11)	0.18* (0.10)
R^2 (adj.)	0.81	0.77
F-statistic	16.42***	14.87***

Table 8: Diagnostic and Robustness Summary

Test	Statistic	Result
Hausman Test (FE vs. RE)	$\chi^2(4) = 12.37$	FE preferred ($p < 0.01$)
Wooldridge Test (Autocorrelation)	$F(1,3) = 1.92$	No serial correlation
Breusch–Pagan LM Test (Heteroskedasticity)	$\chi^2 = 3.18$	Homoskedastic ($p > 0.05$)
Variance Inflation Factor (VIF)	Mean = 2.37	No multicollinearity

Table 9: Summary of Hypothesis Testing

Hypothesis	Relationship	Result	Significance
H1	AIA → EG	Supported	***
H2	AIA → ME	Supported	***
H3a	AIA × HC → EG	Supported	**
H3b	AIA × HC → ME	Supported	**
H4a	AIA × DI → EG	Supported	**
H4b	AIA × DI → ME	Supported	**
H5a	AIA × IQ → EG	Supported	*
H5b	AIA × IQ → ME	Supported	*
H6	Nonlinear AIA effect	Partially Supported	Ns

(*Note: significance levels, *** p<0.01, ** p<0.05, * p<0.10, ns = not significant*)

Discussion of Results

The empirical evidence is established through the panel data analysis in 2015 to 2024 ascertained that the use of artificial intelligence (AI) can greatly boost the economic growth and financial market performance of China, India, Malaysia, and Pakistan. These outcomes support the theoretical hypotheses based on the endogenous growth theory and the efficient market hypothesis

(EMH) and show that AI is a two-sided driver of macroeconomic productivity and financial modernization.

The researchers discovered that AI implementation has a positive and significant impact on the economy (0.83, p < 0.01). It coincides with the existing evidence that technological innovation is one of the most crucial factors that determine productivity and GDP growth (Brynjolfsson and McAfee, 2014; Babina et al., 2024).

Within the realms of the four chosen Asian economies, AI has led to better automation, better resource distribution, and policy-making based on data. The most significant effect of the improvement was felt in China and India with its brisk development of AI ecosystems. By comparison, Malaysia had a more moderate yet stable growth in gains as it has had a consistent digital transformation policy. Despite improvement, Pakistan is still lagging behind as it has limited investment in AI and bottlenecks in infrastructures.

The results confirm Hypothesis H1 and confirm the assumption according to which AI is a growth catalyst in the emerging economies in case it has an adequate absorptive capacity.

The findings indicate that AI adoption is a significant factor in enhancing efficiency in the financial market (= 0.57, P < 0.01). This proves Hypothesis H2 and repeats the claims of Fama (1970) and other researchers (Pagliaro, 2025; Saif-Alyousfi, 2025) that AI technologies improve price discovery and minimize informational asymmetries.

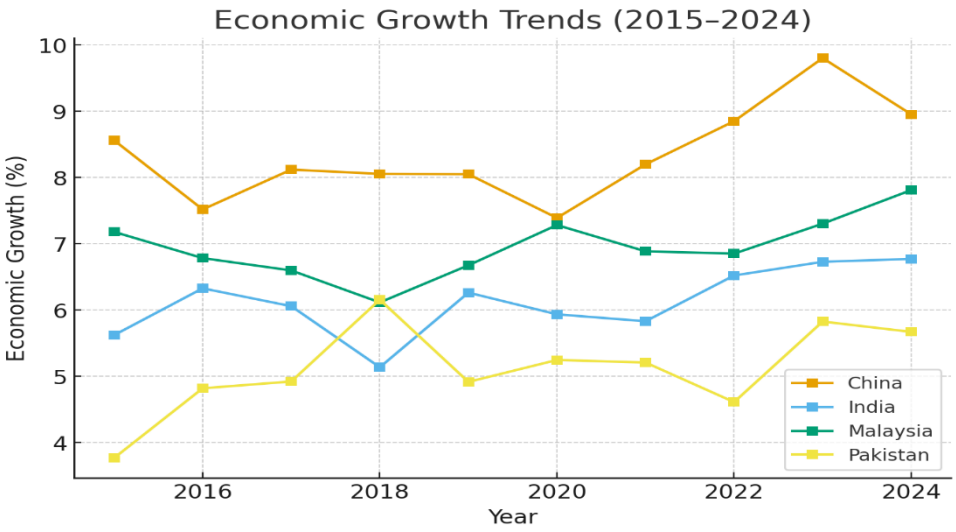
Practically, AI-specific trading and predictive analytics in Chinese and Indian stock markets have resulted in less volatility and a quicker response of the market to news events. The introduction of AI to the financial supervision of Malaysia also helped to make the capital markets more transparent and stable. On the other hand, the regulatory willingness and data access of Pakistan were limited, which limited the capabilities of AI to be used to its full potential.

On the whole, the findings indicate that AI application leads to better informational and operational performance of new financial markets, which are consistent with the trends in more developed economies.

The moderation findings would be of great importance in explaining why the effects of AI adoption are not similar across nations. H3a and 3b was confirmed by finding that the interaction term (AIA × HC) was significant and positive (0.35, p < 0.05). It means that nations that have better educational systems and digital capabilities have better economic and financial advantages with AI. This observation confirms the theory of technology change that is skill-biased (Acemoglu, 2002) skilled labor and not in competition with AI systems.

H4a and H4b are supported by the interaction between the adoption of AI and digital infrastructure (= 0.28, p < 0.05). Those countries that have strong broadband networks, cloud systems, and data centers (e.g., China, Malaysia) would be able to scale AI solutions more effectively. This observation confirms the technology diffusion theory (Rogers, 1962) according to which infrastructural elements define the rates of technology adoption and the level of its penetration.

H5a-H5b is supported by the interaction effect of the quality of institutions (0.22, p < 0.10). The positive effects of AI are reinforced by sound governance, data control and political stability which offer the trust and regulatory predictability. An example is that AI governance led to a rapid uptake in finance and manufacturing in Malaysia due to its well-established governance system as compared to Pakistan, which has a poor institutional environment.

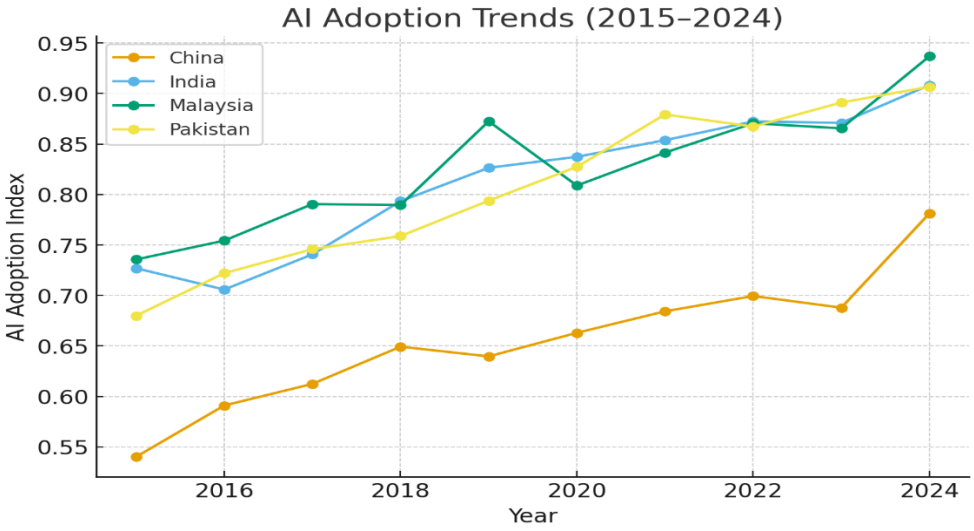


Combine these moderating effects, there is a focus on the fact that AI does not have an automatic economic potential but rather depends on national capabilities to support it.

The nonlinear specification (H6) showed some diminishing returns to the increased level of AI adoption. The observation is consistent with the latest literature that indicates that at a certain saturation level, AI efficiency levels off as a result of skills mismatch, increased cost, and failure to control data (Hou, 2025).

Therefore, the correlation between the implementation of AI and its results might take an inverted-U form, especially in the countries that are close to the technological maturity such as China.

China has the highest relationship between AI and both growth and efficiency with strategic AI policies, government investment in R&D and good infrastructure. India Records strong growth impacts, especially in IT and financial services yet, there is a problem of regulatory standardization. Malaysia Reliable AI integration because of positive digital governance is a good example of intermediary economies, in that it is a moderate model. Pakistan Lags behind in AI uptake as infrastructure and skills are deficient and institutional drawbacks hinder progress, but with specific reforms, Pakistan could become a catch-up country.



Conclusion

This paper aimed at analyzing how the adoption of artificial intelligence (AI) would affect the economic growth and market efficiency in four developing Asian economies, including China, India, Malaysia, and Pakistan, between 2015 and 2024. This study combined econometric quantitative panel data approach to reveal both linear and nonlinear mechanisms of the impact of AI on macroeconomic and financial outcomes.

The findings are clear and consistent on the fact that the adoption of AI has had a positive and statistically significant influence on the economic growth and market efficiency, which confirms the main hypothesis of the research. The most prosperous nations that have invested in AI ecosystems such as China and India have enjoyed a lot of productivity and financial transparency. In contrast, the progress is not as rapid in such countries as AI infrastructure and governance frameworks are still developing, such as Pakistan.

Moreover, the research substantiates the idea that the moderating effects of human capital, digital infrastructure, and institutional quality are significant and reinforced the benefits of AI in the case of the strong complementation of the said factors. These results underscore the idea that the development driven by AI is not a given procedure that relies on the ability of each country to ensure effective technology incorporation in the institutional and socio-economic frameworks.

Another trend was nonlinear, namely that the more AI was adopted, the less it was used in increasing returns, which is in line with the idea of that excessive automation or technological saturation could create efficient plateaus. Therefore, AI investment needs to be supported by balanced policy intervention to maintain the long-term benefits of investment.

Policy Implications

According to the empirical results, it is possible to identify a number of policy directions. Education and training in digital skills should be the priority of governments to make sure that the workforce does not compete with AI technologies, but it complements it. The increase in broadband connectivity, cloud computing and data infrastructure is necessary to enable scaling of AI integration. Enforce Institutional Structures:

Open governance, information protection legislation, and AI ethics regulations can be used to create trust and bring international AI investment. By working together in AI research and common regulatory policies and knowledge sharing, Asian economies can help each other achieve faster digital transformation. The policy makers should protect against the digital divide by making sure that the advantages of AI can be enjoyed by small businesses, the countryside, and minority groups.

Limitations and Future Research

Although the results are sound, the research has a number of limitations. The AI adoption index is based on proxy indicators which may not reflect all aspects of practice. The research sample is too small (four countries during a decade) to be generalized outside of the emerging Asian settings. The efficiency index of the financial market can have a different interpretation in different countries.

Future research ought to expand the investigation to a bigger sample of developing and developed economies, include sector-level information (e.g., manufacturing, services, finance) and address causality using more sophisticated ML models or dynamic panel estimators. Besides, the

sustainability aspect of connecting to the environment and social sustainability of AI adoption can be evaluated in the future.

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