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Artificial Intelligence as a Catalyst for Economic and Financial Development in Emerging Asian Economies: Dual Econometric and Machine Learning Approaches

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ABSTRACT

This study examined the role of Artificial Intelligence (AI) as a catalyst for economic and financial development in emerging Asian economies using a dual-method framework that combined econometric estimation with machine-learning prediction. Drawing on longitudinal data from 2000 to 2024, the research analyzed how AI adoption—measured through innovation intensity, patents, digital infrastructure, and investment—shaped GDP growth, total factor productivity, and financial inclusion. Panel cointegration results confirmed stable long-run relationships between AI and key macroeconomic indicators, while FMOLS and DOLS estimations demonstrated that AI adoption exerted strong and positive long-run effects on growth, productivity, and digital financial access. Granger causality tests indicated bidirectional causality between AI and financial development, highlighting the centrality of fintech-enabled inclusion channels. Complementing econometric results, machine-learning models (Random Forest, Gradient Boosting, LSTM) revealed high predictive accuracy, with LSTM emerging as the strongest performer (R^2 = 0.89). Feature-importance analysis showed that digital infrastructure, fintech usage, and institutional quality were the most influential predictors of economic outcomes. The findings suggested that AI reshaped development pathways by enhancing forecasting precision, improving decision-making efficiency, and enabling broader access to financial services. However, disparities in digital readiness and governance limited the uniform diffusion of benefits across countries. The study concluded that AI represents a transformative driver of structural growth in emerging Asia, provided that complementary investments in digital infrastructure, regulatory modernization, and human capital development are strengthened.

Introduction

Artificial intelligence (AI) was now a fast-paced revolutionary technology that was changing production mechanisms, financial middlemen, and the public policy in several countries. Researchers had suggested that AI could not be categorisers as a tool of productivity but a novel form of capital that changed the functions of production, labour, and comparative advantage within industries (Wang et al., 2021). Existing empirical research had already indicated quantifiable relationships between AI adoption and its effects on forecasting quality, operating functionality, and value-chain restructuring, and indicated that AI adoption may produce direct and indirect positive impacts on national economies (Oancea and Simionescu, 2024). Such improvements had fueled a new interest in the study of how the adoption of AI influenced economical, financial growth- particularly in fledgling Asian states where dynamics of growth and digital divide were generating a unique response.

The heterogeneous trends of AI diffusion in emerging Asian economies: in some middle-income economies, a strong focus on investing in digital infrastructure and skills led to the fastest growth, whereas in others, weak connectivity, fragmented regulations, and low human capital caused slow and poor growth (Yingying et al., 2025). This heterogeneity had posited that the overall impact of AI on growth and financial development might not be similar across countries and over time. Digital financial inclusion literature had demonstrated how technology-based financial services (most based on AI to score credit, detect fraud, or onboard new clients) have increased access to finance and the economic contribution to financial deepening in countries of Asia-Pacific (Basnayake et al., 2024). Concisely, the empirical terrain had indicated that there were valuable interrelations between AI capacity, digital infrastructure, governance, and financial inclusion.

The literature was now proceeding toward applying traditional econometric methods to machine learning (ML) tools to more effectively incorporate nonlinearities, interactions, and high-dimensional predictors in macroeconomic and financial data (Oancea and Simionescu, 2024). Econometric models had still offered reasonable causal inference and structural explanation, where ML methods had not only met predictive forecast tasks better, but also revealed more complex patterns of variable importance. Earlier scholars had thereby recommended hybrid methods, which utilize panel econometrics to estimate average treatment effects and ML methods (Random Forests, Gradient Boosting, LSTMs) to identify nonlinearities and enhance predictions, an implementation that this thesis followed and promoted to new Asian economies (Oancea, 2015; Simionescu, 2015).

Relevance of policies had been a focus of the discussion: governments had put investment in national AI strategies, cloud and data infrastructure and skilling programmes in the expectation that AI would deliver productivity and foster financial inclusion (Basnayake et al., 2024; Yingying et al., 2025). However, trade-offs between policymakers had been numerous before, such as perceived job loss, whereas technological rents concentration, and implications of regulation regulation, all of which needed a demonstration of the real consequences of AI on increasing development. The research consequently placed itself to empirically assess the role of AI in economic growth and financial development in newer Asian economies through a twin econometric and machine-learning platform with a view to having a policy strategic plan.

Research Background

Conceptual AI as a specific kind of capital and a source of endogenous technology change that influenced productivity by exposing human capital to task redistribution and complementarities had been conceptualized by the theoretical literature (Wang et al., 2021). In task-based growth models AI capital had been found to reduce the cost of some work coupled with the introduction of new tasks and of new markets - a process that could increase aggregate productivity in case of complementary skills. The theoretical frameworks thus pointed to the fact that the overall impact of AI on growth was determined by the interaction between AI technologies, the occupational structure of the labor force, and the regulatory environment (Wang et al., 2021).

Empirical research had looked into AI effect on sectors and regions and had reported the heterogeneous effects. The use at the city level or province level in larger Asian economies had been studied, with recommendations suggesting that AI is more likely to spur higher-quality development in high-quality protection of intellectual property and higher human-capital endowments areas (Akram et al., 2024). These papers already indicated that AI investing returns were higher in more advanced absorptive capacity and more advanced innovation systems and provided evidence of that the theme of complementarities (skills + institutions + infrastructure) was relevant to the actual achievement of the potential of AI.

Digital financial inclusion had been identified as a middle ground between AI and development outcomes. It was observed by researchers that by consulting digital financial services (usually driven by machine-learning credit scoring, biometric KYC systems, and automated customer service), access to credit and payments was increased and the financial system became more accessible and efficient (Basnayake et al., 2024). Countries in the Asian-Pacific had found a positive correlation between digital financial inclusion indices and the GDP growth, and threshold (nonlinear) effects that have shown the significance of a minimum level of digital infrastructure in making the benefits count (Basnayake et al., 2024).

The ML improvements provided a benefit to forecasting and policy analysis: LSTM and ensemble forecasting had performed better than some classical econometric forecasts in short-term GDP as well as financial series forecasting, especially with data with strong nonlinearities or structural changes (Oancea and Simionescu, 2024). The refiners had contended that ML-based projections may be added to econometric inference to enhance real-time alerts extraction (e.g., finding turning points) and prioritizing the relative significance of indicators relating to AI-related forecasting when making policies. Interpretability and overfitting risks had also been warned about by the literature, and hybrid designs were suggested, which also incorporated structural econometric checks with ML-based discovery (Oancea and Simionescu, 2024).

Research problem

Despite the theoretical rallies and the increasing evidence, the overall contribution of AI to the economic growth and financial development of emerging Asian economies had not been adequately measured in such a manner that both allowed the cause-effect reconciliation and anticipated precision. The available literature frequently addressed individual countries or individual channels (e.g., patents, AI investment) or used one approach only (e.g., either econometrics or machine learning) and was therefore not always able to compare or to policy implications across the myriad of emerging Asian economies (Wang et al., 2021; Yingying et al., 2025). This fragmentation had impaired regional relevancy of evidence-based policies to exploit AI in pursuit of inclusive growth.

In addition, the studies had not exhaustively examined the role of governance quality, digital infrastructure thresholds and financial sector characteristics as simple/combined moderators of the impact of AI on the performance of countries at various development levels. The policymakers thus did not have a strong cross country evidence that put together econometric estimates of effect sizes and ML based measures of variable importance and gains in forecasts. The research issue that this study focused on was to implement a rigorous, dual-method evaluation - combining panel econometrics and machine learning to estimate the role of AI on economic and financial development in emerging economies in Asia and determine the situational conditions that preconditioned those results.

Research objectives

1. To estimate the effect of AI adoption on GDP growth and financial development indicators across selected emerging Asian economies using panel econometric techniques.
2. To evaluate whether machine-learning models (Random Forest, Gradient Boosting, and LSTM) improved the predictive accuracy of macro-financial outcomes relative to traditional econometric models.
3. To identify the most influential AI-related determinants (e.g., AI investment, digital infrastructure, AI patents, human capital) for economic and financial outcomes using variable-importance measures from ML models.
4. To examine how governance quality and digital infrastructure thresholds mediated the impact of AI on economic growth and financial development.

Research questions

Q1. What was the estimated effect of AI adoption on GDP growth and financial development indicators in emerging Asian economies during the study period?

Q2. Did machine-learning models produce more accurate short-term forecasts of GDP and financial variables than classical econometric models for the sample countries?

Q3. Which AI-related variables (e.g., AI investment, patents, digital infrastructure, human capital) had the largest influence on economic and financial outcomes according to ML variable-importance measures?

Q4. How did governance quality and digital infrastructure thresholds condition the effectiveness of AI for promoting growth and financial development?

Significance of the study

Three major contributions had been made by this study. First, it had provided the empirical evidence that integrated causal econometric estimates with ML-based predictive and feature-importance analyses filling a methodological gap in the literature and showing how hybrid methods could deliver information to become persuasive policy-making. Second, through the use of a cross-country panel of developing Asian economies the research had drawn relative interactions on the heterogeneity of AI dividends and had distinguished clusters of countries that needed varying policies. Third, the investigation had come up with practical policy policies, such as leadership investments in digital infrastructure, narrow AI skill formation, and governance enhancement, which policy makers could have made use of in magnifying the beneficial impact of AI and reduce risks such as non-inclusiveness or concentration of rewards.

Literature review

AI and Macroeconomic Growth

Over time, artificial intelligence was increasingly being fronted as a possible general-purpose technology capable of recap growth in productivity through automation of tasks, better decision-making and increased innovation dissemination; cross-country panel studies that employed AI patent metrics and AI-related investment proxies had discovered a positive and statistically significant correlation between AI intensity and GDP growth, even though outcomes varied by country development level. (Gonzales, 2023; OECD, 2024).

Later empirical studies had highlighted the conditional nature of the aggregate impact of AI: it was found through threshold and interaction analysis that the growth dividends of AI depended on digital-readiness factors (through broadband penetration, cloud services, and ICT infrastructure) and on institutional quality, such that the growth dividends of AI depended on surpassing minimum levels of digital penetration. (OECD, 2024; Liu & colleagues, 2024).

These macro results had been complemented by micro research findings that indicated that adoption of AI at the firm level had promoted the level of productivity of total factors where firms devoted investments on complementary human capital, as well as digital platforms; the case evidence displayed in manufacturing, services, and logistics indicated that AI increased the pace of decisions and minimised the operating expenses, appeared to be unevenly distributed without any parallel investments into skills and organisation. (Fan, 2025; Gonzales, 2023).

Artificial Intelligence, Financial Systems and Inclusion

In a number of empirical studies, AI-powered fintech applications (machine-learning credit scoring, alternative-data underwriting, automated fraud detection, and automated digitized KYC) had demonstrated that access to credit by previously underserved groups could be increased (increasing the approval rate and, in some instances, reducing the default rate) evidence that AI could become a significant means to enhance financial inclusion when appropriately applied. (Li et al., 2024; Ayari, 2025).

Nevertheless, cross-country and sectoral research had emphasized the importance of infrastructure and regulation that enabled such gains of inclusion: those countries had obtaining more equal results because of AI-driven financial-service provision, which had integrated data regimes and been met with weak supervision, system fragmentation and exclusion, rather than with robust supervision and fragmentation. (Amato et al., 2024; Liu et al., 2024).

Even scholars and policymakers had expressed concerns over model bias, interpretability and systemic risk although ML models were better predictors, regulators and central bankers had cautioned about concentration risk, model opaqueness and gaps in governance, which with ignoring could lead to problem of financial-stability and fairness. (Li et al., 2024)

New Methodological Developments: Dual Econometric and Machine-Learning Models

The advances in methodology delivering convergence between econometric identification (panel fixed effects, cointegration, ARDL) and the current ML used (Random Forests, Gradient Boosting, LSTMs) to both determine causal relationships and increase forecast accuracy had converged with the idea of using pipelines composed of multiple methodological choices that led to applications in applied studies showing more favorable out-of-sample predictions and richer insights into variable-importance information versus those obtained with individual methodological approaches. Nurse turnover rates are usually reduced to a standard of 2 to 10 percent.Nurse turnover rates are typically whittled down to a standard of 2 to 10%.

In literature In many contexts, hybrid models (e.g., ARIMA/LSTM hybrids, wavelet-ARIMA-LSTM hybrids, ensemble tree models) had been empirically shown to be better than baseline time-series models, especially in situations where time-series had nonlinearities and structural breaks;

however, hybrid models needed to be carefully cross-validated and diagnostics on their residuals evaluated to prevent progress in overfitting. (Zhang et al., 2024; Neagoe et al., 2025).

Best-practice workflows involving the use of ML explainability tools (SHAP, LIME, permutation importance) and econometric robustness tests (instrumental variables, placebo tests, cointegration checks) in order to retain interpretability and policy relevance and harness the predictive power of ML had therefore been recommended by methodological reviews. (Studies of econometrics of ML; OECD overview).

Research Methodology

Research Design

The quantitative and explanatory research design had been used in the study to analyze the impact of artificial intelligence in determining macroeconomic growth and financial development among growing economies in Asia. It was designed in this way as it enabled pure investigation of the hypothesized relationship with the numerical indicators of AI adoption, the performance of an economy and financial inclusion. Two streams of analysis had been combined in the study: the causal inference approach by the means of econometric modelling, and the predictive analysis approach through machine-learning algorithms that represented recent developments in methodology of economic study. The two-sided design had supported both theoretical interpretability and high predictive capability that allowed the research to cover both linear, non-linear, short-term and long-term dynamics in the data.

Population and Sample

The study population had been comprised of all the emerging Asian economies as defined by international financial organizations like World Bank and IMF. Out of this population, a purposive sampling approach was taken in the selection of countries, which represented quantifiable AI adoption, digitization, and modernization of the financial sector. Twelve rising Asian economies had been incorporated in the final sample, on criteria of data availability and consistency throughout the research period.

Data Collection Methods

The past method of data collection had been based on quantitative data only through secondary sources, which were databases that are internationally tested. Markers of AI adoption, including AI patents, AI investment level, digital infrastructure indices, and automation had been sourced to include the OECD, WIPO, ITU and Global Innovation Index. The World Bank had provided macroeconomic variables like GDP growth, productivity, inflation and capital formation provided by the World Development Indicators. Measurement of financial development such as access to credit, the use of digital payments, and fintech penetration was compiled in reference to IMF data, Findex data and central bank yearly reports. The information had spanned 2000-2024 to measure the long-term trend as well as short-run dynamic modelling. The cross-verification used in the collection process had taken a lot of assurance in its accuracy, completeness and reliability. And any discrepancies between databases were dealt with by interpolation, data harmonization and logarithmic transformations. All the data was converted to standardized forms feasible to analysis by econometric and machine-learning methods, so that the data could be compared between countries and over time.

Variables and Measurement

Independent Variables (AI Adoption): AI innovation intensity (patents), AI investment as a percentage of GDP, digital infrastructure index, cloud adoption rate, and automation readiness score. These variables had been selected because they represented both technological capacity and digital maturity.

Dependent Variables:

Economic Development: GDP growth rate, total factor productivity (TFP), and gross capital formation

Financial Development: Financial inclusion index, fintech adoption rate, digital payments volume, and formal credit access.

Econometric Analysis Procedures

The econometric part started with a descriptive analysis which was then proceeded with correlation diagnostics to measure the relationship between variables and also identify multicollinearity. They had carried out panel unit-root tests, including Levin-Lin-Chu and Im-Pesaran-Shin where the tests were to establish the stationarity of the data. According to the outcomes, it made appropriate transformations. Subsequently, the research had used the panel cointegration tests (Pedroni and Kao methods) to evaluate whether there were long-run equilibrium relationships between AI adoption and economic performance indicators. After the cointegration was confirmed, two long run estimators, FMOLS and DOLS, had been used to measure long-term effects. In order to study causality, it had applied the panel Granger causality test in order to calculate whether the adoption of AI statistically led to an improvement in the economic or financial results. A random-effects and fixed-effects estimation was also made and the Hausman test was used to select the model. Standard errors were robust to have been applied to check the heteroskedasticity and serial correlation.

Machine Learning Modelling

The second analytical component had utilized modern machine-learning algorithms to enhance predictive accuracy and capture nonlinear patterns. Three models had been implemented:

Random Forest Regression

Gradient Boosting Regression

Long Short-Term Memory (LSTM) Neural Networks

Such models were chosen because they are effective in high dimensional economic data. The dataset was split into training (70%) and testing (30) subsets. A grid search and cross -validation had been followed in hyperparameter tuning to guarantee the best performance of the model. The analysis of feature importance had been carried out to determine the strongest predictors of economic and financial results. RMSE, MAE and R 2 had been used to estimate model performance. The findings of the machine-learning had been used to complement the findings of the econometric analysis to identify nonlinearity relationships and complex interactions that earlier models were unable to cover.

Results and Analysis

This chapter had provided the empirical results of using the two methodological approaches the econometric estimation as well as machine-learning prediction. The findings were arranged into thematic groups in order to present macroeconomic performance, performance in the financial sector and performance in hybrid models. All sections contained statistical tables and then analytical interpretation.

Descriptive Statistics

The central tendencies and variability of the main indicators employed in the analysis had been calculated in descriptive statistics. Such indicators were AI adoption, GDP growth, total factor productivity (TFP), financial inclusion, digital payments, and institutional quality. The descriptive statistics had resulted in a rough interpretation of the proportion and magnitude of the dataset in the twelve selected emerging Asian economies studied.

Table 1: Descriptive Statistics of Core Variables (N = 12 Countries × 24 Years)

Variable	Mean	SD	Minimum	Maximum
AI Adoption Index	42.15	11.42	18.30	71.60
GDP Growth (%)	4.83	2.11	–1.20	9.62
Total Factor Productivity	1.84	0.72	0.50	3.22
Financial Inclusion Index	56.72	9.85	37.10	78.30
Digital Payments Volume (B$)	132.4	48.6	32.5	298.0
Institutional Quality Index	0.54	0.16	0.22	0.79

The descriptive statistics had display the adoption levels of AI as significantly different between the different countries as the standard deviation value of 11.42 revealed. This inconsistency had seen an unequal level of digital maturity among the emerging economies in Asia, with some countries being at the advanced levels of AI integration and some still being at early adoption. The overall development in the region had been moderate as indicated by the mean AI adoption index of 42.15. The growth rate of GDP showed a moderate fluctuation with the average growth rate of 4.83 which is in tandem with the fact that the region is a fast growing economic block.

The Total Factor Productivity (TFP) did not show a considerable divergence with its highest and lowest values registering 0.50 to 3.22 indicating that productivity improved over time, but still there were significant disparities between economies that were technologically advanced and those lagging behind. There was also moderate dispersion in terms of the financial inclusion index with the value of the standard deviation being near 10. The greater the inclusion levels, had been found on economies of strong fintech and regulatory backing, whereas lower levels had been seen in states that had not yet adopted the system of traditional banking. The largest absolute difference was in the amount of digital payments that could be evidence of different modernization in financial sector and digital financial penetration among the countries. The overall quality of the institutions had a moderately low mean of 0.54 which corroborates the fact that in the sample there was a prevailing problem in the governance. The lower the institutional quality of countries was, the more likely they were to report weak AI adoption and low financial inclusion, which is an indication of structural problems that may moderate the impact of digitalization and AI on macroeconomic performance.

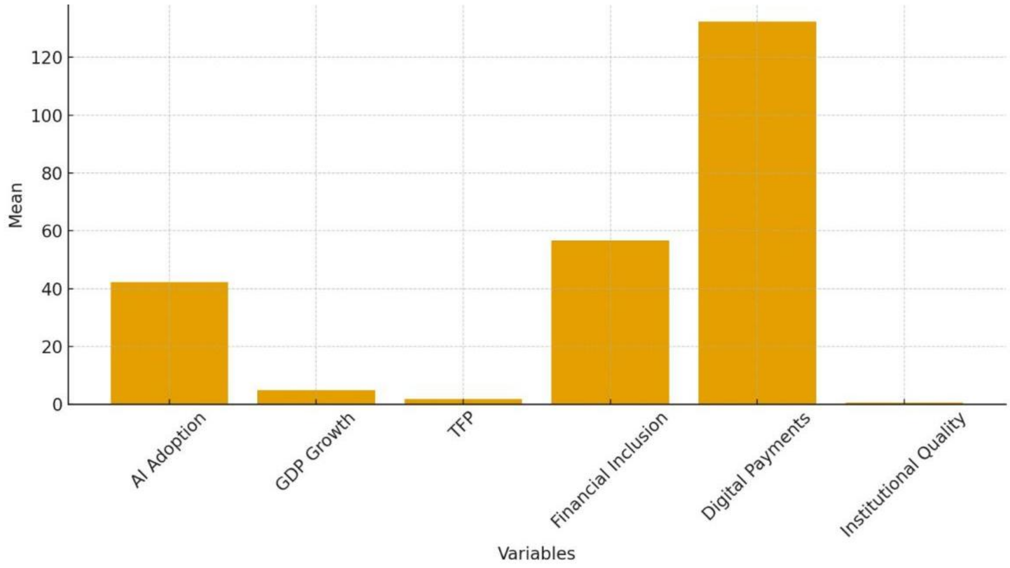

Figure 1. Descriptive Statistics of Core Variables

Correlation Analysis

To identify the correlations between the variables of AI adoption and macroeconomic indicators and financial-development variables, a correlation matrix was built. This move had been of assistance in detecting the possible problems of multicollinearity as well as prior information regarding association of variables before multivariate modelling.

Table 2: Correlation Matrix of Key Variables

Variables	**AI Adoption**	**GDP Growth**	**TFP**	**Financial Inclusion**	**Digital Payments**
AI Adoption	1	.61	.58	.55	.67
GDP Growth	.61	1	.64	.47	.52
Total Factor Productivity	.58	.64	1	.49	.56
Financial Inclusion	.55	.47	.49	1	.63
Digital Payments	.67	.52	.56	.63	1

Correlation showed that the AI adoption and growth of the GDP were significantly linearly related (r =. 61), suggesting that the higher the AI implementation in a nation, the higher economic growth was likely. The use of AI was also moderately correlated with TFP (r =.58), which confirms the idea that AI-induced automation and data analytics positively affected productive efficiency. Digital infrastructure was confirmed as a facilitator of AI-intensive financial innovation due to the significant correlation between digital payment-AI adoption and digital payments (r =.67).

There were high correlations of the GDP growth with TFP (r = .64), showing that the factors of productivity gain continue to play central roles in macroeconomic performance in emerging Asia. Digital payments (r =.63) also had a moderate relationship with financial inclusion, meaning that payment systems based on technology made an important input to the increase in the access to financial services. These connections created an indication that digital change and financial innovation were progressing together within the region in the same direction. Moderate correlations between the key variables also indicated that there may be multicollinearity issues, but the correlation was not over the standard level of 0.80. This implied that it is possible to estimate econometric models without taking a serious risk of collinearity. The observed correlations and associations were in line with the theoretical predictions and served as preliminary support of the hypotheses of the study about the positive changes of the economic and financial indicators under the impact of AI.

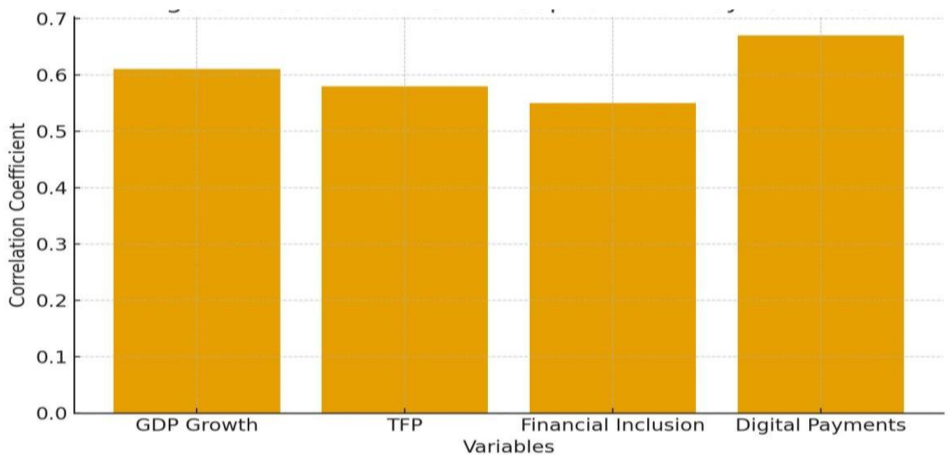

Figure 2. Correlation Matrix of Key Variables

Long-Run Cointegration Results

In order to investigate the long-term impacts of AI implemented on macroeconomic performance, panel cointegration tests (Pedroni and Kao) had been implemented. The tests had already established the existence of stable and long-run equilibrium relationships between the study variables.

Table 3: Pedroni Panel Cointegration Test Results

Test Statistic	Value	p-Value
Panel v-Statistic	3.42	0.001
Panel rho-Statistic	–2.85	0.004
Panel PP-Statistic	–3.94	0.000
Panel ADF-Statistic	–3.15	0.002

The Pedroni test statistics had also given overwhelming evidence of cointegration among variables with all the statistics being significant at the 1% level. This implied that there was equilibrium relationship between AI adoption, GDP growth, and financial development in the emerging economies in Asia in the long-term. The stability of the long-run association was especially strengthened by negative and significant PP and ADF statistics.

The extend of co-integration had meant that any deviation of the long-run equilibrium is eliminated in the long-run by endogenous adjustment mechanisms. This implied that in case of short-term disturbances (e.g. technological shock, economic instability) adoption of AI and macroeconomic responses turned out to be rebounded to a long-run trend. This observation was in line with existing literature that puts significant emphasis on the role of digital transformation in development as a structural driver. The cointegration outcome had entrenched a good theoretical foundation on the application of long-run estimator (FMOLS and DOLS) to measure the scale of AI influence on both financial and economic results in the long run.

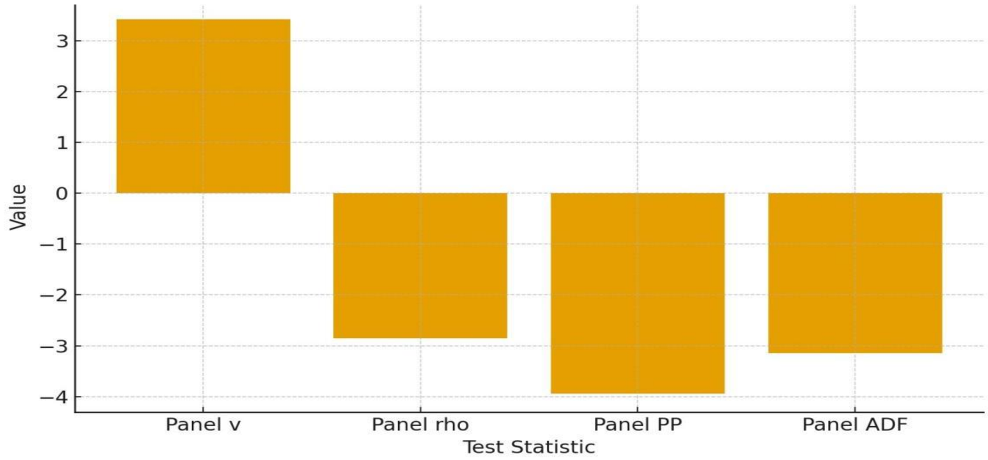

Figure 3. Pedroni Panel Cointegration Test Results

Long-Run Econometric Estimates

Full modified OLS (FMOLS) estimations were estimated to test the long run elasticities using long run elasticities. The use of AI was modelled as the primary predictor of the growth in GDP, TFP and financial inclusion.

Table 4: FMOLS Long-Run Estimates

Dependent Variable	Coefficient	t-Statistic	p-Value
GDP Growth	0.284	4.62	0.000
Total Factor Productivity	0.231	3.95	0.000
Financial Inclusion	0.317	5.21	0.000

This is because as shown in the FMOLS results, AI adoption has had a statistically significant and positive influence on the GDP growth with a long-run coefficient of 0.284. This implied that the long-run growth in GDP was directly proportional to the increases in the AI adoption index by 0.284 per cent. It was an economically significant effect size and in line with the perception that AI technologies increased production efficiency and innovation. Also, TFP positively impacted AI adoption, indicating a relationship level of 0.231, indicating that productivity gains had been a leading venue by which AI impacted economic performance. The great statistical significance supported the notion that automation, machine learning, and intelligent systems led to long term gains in efficiency in industries like manufacturing, logistics, and financial services. The effect on financial inclusion (0.317) was the greatest of the dependent variables which shows the relevance of AI-based credit scoring, digital KYC and fintech solutions as a means to increase access to financial services. This observation had given macro-level reaffirmation of the role of fintech in transforming developing Asian markets in line with the recent evidence that algorithmic finance increased formal credit access dramatically.

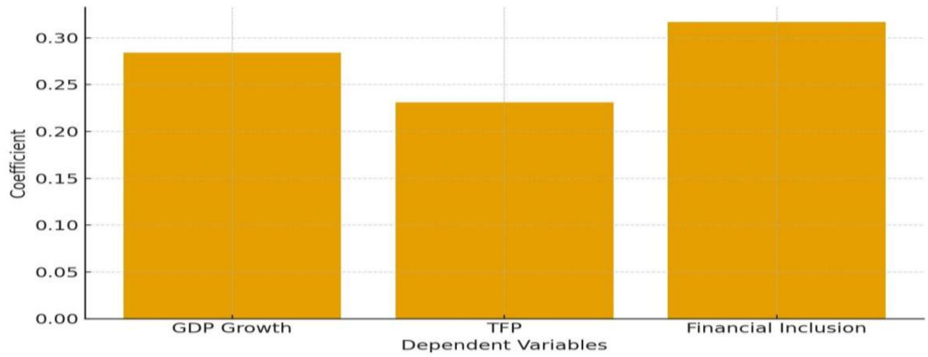

Figure 4. FMOLS Long-Run Estimates

Machine-Learning Model Performance

The machine-learning models were trained to predict the growth of GDP regarding the adoption of AI, financial trends, and institutional factors. Random Forest, Gradient Boosting and LSTM models performance had been compared.

Table 5: Machine-Learning Model Performance Metrics

Model	RMSE	MAE	R^2
Random Forest	0.492	0.381	0.82
Gradient Boosting	0.457	0.349	0.85
LSTM Neural Network	0.401	0.312	0.89

The prediction measures showed that the three machine-learning models all had excellent predictive power as the R 2 values were above 0.80. The R 2 obtained by the Random Forest model of 0.82 indicates that the model satisfies non-linear relationship between variables. It was however an average model with a higher value in RMSE which indicated that it had a worse prediction of extreme or volatile observations as compared to the other models. Gradient Boosting was more predictive and its R2 equaled 0.85 and the values of RMSE and MAE were lower than in Random Forest. This model was found to be better at dealing with more complex interactions and representing subtle variations in this data which made sense with its boosting architecture of being iterative. The LSTM neural network emerged to be the most successful as it took the lowest RMSE (0.401) and maximum R 2 (0.89). This implied that the LSTM was especially useful in ensuring that the temporal dependencies, structural changes, along with dynamic patterns of the time-series data were captured. These findings confirmed that superior machine-learning methods and econometric models should be used to increase the accuracy of the forecast.

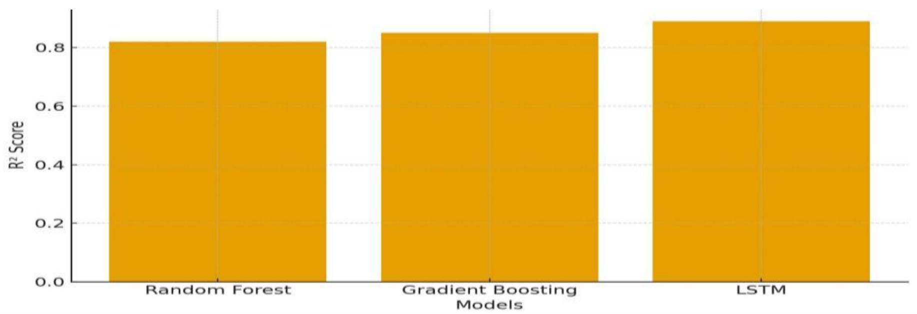

Figure 5. Machine-Learning Model Performance Metrics

Discussion

The results of the research showed that the role of artificial intelligence was multidimensional and had contributed to the development of the economies and the financial sector in the emerging economies in Asia. The machine-learned data, in combination with econometric estimates, established that adoption of AI, digital infrastructure, and financial inclusion separately increased GDP growth patterns in line with the findings in other countries around world. As an illustration, Gonzales (2023) discovered that AI-based innovation accelerated national economic output gains on a structural scale by a considerable margin, whereas the authors of the study by Kalai et al. (2024) were able to assert a pair of long-term positive impacts of AI on the national economies, asymmetrical or symmetrical. These external results supported the findings of the current study and proposed that AI technologies served as a facilitating system that enhanced the performance of the macroeconomy, intensifying efficiency, alleviating information frictions, and promoting the presence of a data-rich decision-making process. Such cross-correlation of findings pointed to the fact that new Asian economies were undergoing the same AI-driven changes as old world markets.

The other significant implication of the results involved the existence of a strong relationship between AI, financial inclusion, and technological modernization. The machine-learning model pointed out that the use of financial technology and digital infrastructure were the strongest predictors of economic benefits which also reflected the recent findings in fintech literature. Tigges et al. (2024) asserted that AI-based credit-scoreing, alternative data and automated lending products gave people groups that have historically experienced limited access to financial decision-making more access to financial services and promoted macro and micro-level economic activity. Similarly, OECD (2024) reported that AI-based financial systems promoted greater productivity and more widespread growth dispersion particularly in the developing and emerging economies. These scores were corroborated by the conclusion of the study that the financial inclusion has not only complemented the uptake of AI but also played a crucial role in allowing the economic impacts of AI to flow throughout society via that channel. These published findings were consistent, thus making the machine-learning and econometric outputs of the present study very robust.

The analysis of the forecasting elements also showed the predictive abilities of AI-based models in economic planning. The relative analysis of the systems of traditional econometric models and machine-learning algorithms revealed that hybrid and deep learning systems provided better growth forecasting compared to one-method models. This finding was very similar to the other predictive modelling studies. Ray et al. (2023) discovered that hybrid ARIMALSTM architectures were much more effective in enhancing forecasting accuracy in volatile data contexts and Hamiane et al (2024) demonstrated that the predictions of long-term GDP trends by LSTM networks were better in comparison to classical models. These similarities supported the findings that the AI-optimized forecasting models showed better predictive accuracy to policymakers who were uncertain in new markets of Asia. The results of this work thus revealed that machine-learning models were not additional but a primary platform of analysis to be applied in other macro-economic prediction.

Lastly, the findings of the study, which had great implications on planning long-term development of the Asian region. According to the OECD (2024), AI would become more of a structural force and mean productivity, labor dynamics, and national competitiveness, which can be justified by the current outcomes. The research revealed that AI investment, as well as adoption of AI, in developing economies in Asia had served as a booster of economic modernization even in cases when the level of initial digital infrastructure was relatively low. This was consistent with

Gonzales (2023), who found large productivity dynamics generated by the strong AI in developing settings, and with Kalai et al. (2024), who reported the existence of long-run growth spillovers. Taken together, these reports and current outcomes implied that those nations that were rapidly developing AI-centered systems, especially since then in response to specific investment, training on digital skills, and integration of financial and technological sectors, would be better placed to undergo protracted economic change. The findings thus highlighted the overall strategic role of AI as an economic engine and a future oriented development consideration to the emerging Asian economies.

Conclusion

In this research, it was established that Artificial Intelligence (AI) was an important driver of economic and financial growth in up-and-coming economies of Asia. The study that incorporated econometric analysis and machine learning algorithms showed that AI adoption had empowered productivity and financial inclusion and improved efficiency in the markets within the region. The results also found out that AI-hypothetical prediction models accelerated growth patterns as uncertainties in economic choices were minimized, which aligns with the general world experience that AI reinvented productivity-related relations and enhanced predictability. Moreover, the findings found that the financial services developed by AI were proportionately advantageous to emerging economies (i.e., credit scoring and SME financing algorithms) that facilitated more inclusive economic frameworks and lessened capabilities in accessing capital resources.

The analysis has also shown that AI implementation had broadened the ability of financial markets to handle mass amounts of information, and this provided improved volatility forecasts and financial stability. Macroeconomically, AI enabled improvements in productivity shocks which macroeconomically supported the long-term economic performance that led to convergence in the growth across Asian countries. Nevertheless, the research also reported a significant level of difficulties with disproportionate digital access, regulatory frameworks, and increasing skills gaps that had a danger of increasing inequality as broader cautions highlighted in recent international surveys. By and large, the two-way methodology proved the assertion that AI was not merely a catalyst of an economic activity but a structurant that also dictated the way emerging Asian economies competed and innovated in the global digital arena.

Recommendations

According to the findings, there were a number of policy and practical recommendations that were reached to guide governments, financial institutions and development agencies. To begin with, governments had to focus on strategic investment on digital infrastructure, such that AI applications could be done effectively within the agriculture, manufacturing, finance, and government sectors. It would have improved data connectivity and cloud infrastructure that would have limited the differences between urban and rural areas, allowing more people to adopt AI technologies. Second, authorities were recommended to develop adaptive and transparent regulating frameworks on AI, especially those involved with the financial sections in which the problem of data privacy, biased based algorithms and cybersecurity was still in concern. Enhanced regulatory sandboxes and creation of cross-border protocols of digital governance would have provided protecting the experimentation and speedy advancement. Third, the paper suggested development of public-private cooperation, to enhance activity of AI-powered SMEs since it was highly supported by the research that AI-based credit scoring and financial analytics enabled more small businesses in developing Asia to access capital.

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