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Dynamic Determinants of AI Readiness in ASEAN

A System GMM Approach on Productivity and Network Infrastructure

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Abstract
Using a panel regression framework based on Difference and System GMM estimators developed by Arellano-Bond and Blundell-Bond, we investigated the dynamic relationship between AI Readiness, Productivity, and Network Infrastructure among six ASEAN member countries (Singapore, Malaysia, the Philippines, Indonesia, Thailand, and Vietnam). The findings of this study highlight that productivity growth remains the most critical driver of AI readiness in ASEAN, whereas enhancements in network infrastructure alone are insufficient without corresponding advancements in innovation capacity and digital skills. In addressing endogeneity and unobserved heterogeneity, the model conveys that lagged productivity exerts a strong and positive influence on AI readiness, while the effects of network infrastructure and AI implementation are mixed and, in some cases, statistically insignificant. Diagnostic tests, including the Arellano-Bond autocorrelation and Conditional Likelihood Ratio (CLR) test, confirm the validity and robustness of the instruments, confirming model reliability. The study contributes to the understanding of AI-driven development dynamics in emerging economies and supports policy formulation aligned with UN SDG 9 (Industry, Innovation, and Infrastructure) to advance sustainable technological growth and regional competitiveness.

Keywords
AI readiness, productivity, network infrastructure, system GMM, ASEAN

INTRODUCTION

The countries in the Association of Southeast Asian Nations (ASEAN), which share a focus on establishing a consistent governance and ethics framework, articulated by initiatives like the ASEAN Guide on AI Governance and the Responsible AI Roadmap for 2025-2030, intend to alleviate these gaps and drive inclusive AI-driven growth across the region. As a whole, ASEAN expects AI to contribute between 10% and 18% of regional GDP by 2030, translating to almost $1 trillion, with critical sectors such as agriculture, healthcare, and manufacturing set to benefit (Policy Brief, n.d.). However, uneven infrastructure, fragmented regulatory frameworks, and talent shortages across member states present challenges for AI scaling. The AI Readiness Index among ASEAN countries in 2025 discloses critical differences across the region (Tun et al., 2025). Singapore leads the ASEAN region and ranks 2nd globally with an overall AI readiness score of 28.5, driven by its strong regulatory framework (score of 9.8), AI diffusion and adoption (8.0), and investment in human capital (5.8) (Staff, 2025). While displaying steady progress and a national AI strategy, Indonesia scores 17.6 below the global average of 22.1, with notable gaps in AI investment (0.3) and innovation (0.2). Vietnam ranked top 5 in ASEAN in the 2024 Government AI Readiness Index. Globally ranked 5th in AI acceptance and 3rd in AI trust. Vietnam has had a National Strategy on AI since 2021 (Pham et al., 2024).

A major challenge across the region is human capital, with workforce readiness being one of the weakest dimensions (Oswald (eds.) et al., 2019), as some member countries' scores fall below the global average, requiring significant upskilling and education programs to build a capable AI talent pool (Khan et al., 2025). For ASEAN, the significant gap between AI resilience and preparedness (Rane et al., 2025), with the regional overall levels only just above the world average as of 2021, signifying a slow calibration to rapidly changing AI technologies. While governments are proceeding with policy and vision (Valle-Cruz et al., 2019), this is often not accompanied by enough digital adaptability and capacity within the public sector, and national AI strategies beyond a comprehensive framework remain limited or in early stages of development. A central issue is underinvestment, with AI spending in ASEAN estimated at only $2 per capita in 2019, clearly lower than the $155 per capita invested in the US, which impedes the development of the local technology sector innovation capability (Seth et al., 2022). The development of local AI technologies and business adoption lag significantly behind, creating a dependency on external creators instead of domestic innovation (Wibowo et al., 2025). This leads to an explicit internal gap within the region's AI preparedness, while consumers and data infrastructure display preparedness to adopt AI (Putra, 2024).

Based on the APO Productivity Database across ASEAN (Productivity Measurement - APO, 2025) members, it is highly diverse, with critical disparities in economic output per worker. Lao, Cambodia, and Myanmar report the lowest regional outputs at $6,748, $3,020, and $3,377, respectively. Middle-income ASEAN economies display more moderate figures, with the Philippines at $9,196, Thailand at $11,834, and Malaysia with $24,862. Vietnam and Indonesia trail with productivity values of $7,151 and $8,949 per worker.

The Network Readiness Index (NRI) 2024 report focuses on ASEAN economies (Countries – Network Readiness Index, n.d.), specifically in the Asia-Pacific region, which are making vital steps by implementing various levels of national resources. Vietnam and Thailand also show substantial progress, ranking 45th and 40th, respectively, with Thailand leading in digital inclusion and Vietnam demonstrating the strong effect of digital technologies on its economy and quality of life. Singapore sustains its position as the most network-ready society in ASEAN and the second globally, displaying astounding strengths in governance and digitally connected businesses. Malaysia shows a strong regional AI performer, ranking 36th worldwide and leading among upper-middle-income economies with distinguished performance in adopting emerging technologies and encouraging a digitally skilled population.

A strong Productivity Index presents resources for AI investment, while a strong NRI offers the digital backbone for its deployment together. They create a virtuous cycle where a productive, well-connected economy can develop and integrate AI more effectively, thus increasing its productivity and network capabilities in the long term. A country's Productivity Index and Network Readiness Index (NRI) are basic, interactive foundations that jointly improve its AI Readiness Index. Simultaneously, the Network Readiness Index, which measures a nation's data ecosystem, directly supplies technological infrastructure, digital skills, connectivity, and technology adoption that AI systems need to function and scale. The Productivity Index, showing economic output per worker, offers the vital financial capital and economic stability necessary to finance ambitious AI research, infrastructure, and development. For instance, Singapore's high labor productivity of over $110,000 per worker furnishes the strong economic foundation that supports its top-tier AI readiness, ranking 2nd globally.

THEORITICAL FRAMEWORK

The relationship between the Productivity Index, the Network Readiness Index, and the AI Readiness Index is examined through the lens of Resource-Based View (RBV) Theory, and the current Technology Adoption and Diffusion Theories.

Ambitions for AI leadership remain elusive, among lower productivity countries that endeavor to allocate sufficient budgets for such strategic technological initiatives. It is clear that financial surplus is a requirement for the significant investments required for AI readiness, including funding to sustain R&D, purchasing high-performance computing facilities, and presenting financial incentives to attract innovative startups and top AI talent (Hagemann, 2023). The Resource-Based View conveys a nation's competitive advantage (Kovanen, 2024); it depicts the capacity to develop and adopt AI, which is determined by its ownership of valuable, rare, and non-substitutable resources. The Productivity Index, measured as GDP per worker or per capita, is a substitute for the nation's tangible economic and financial resources (Alarifi et al., 2015). The Productivity Index and the Network Readiness Index represent two vital categories of these national resources. A high level of productivity conveys that an economy produces significant surplus capital (Qazi, 2025).

A population with strong digital literacy and STEM skills (human capital) furnishes the talent pipeline for developing and managing AI algorithms. The Network Readiness Index (NRI) evaluates key foundations such as digital skills, technological infrastructure within the population, and the integration of digital technologies by business and government (Allakhverdieva, 2021). The Network Readiness Index (NRI) measures a nation's stock of intangible and technological infrastructure (Silva et al., 2022). These elements constitute the essential infrastructure for AI. High-speed broadband and widespread 5G connectivity (infrastructure) and necessary for gathering and transmitting the vast datasets. A high NRI score often depicts a regulatory environment that promotes, which is critical for deploying AI responsibly. In principle, the NRI furnishes the foundational platform upon which AI applications are scaled and built (Wang et al., 2025).

The effect of these two indices is described by their interdependence. A nation with a strong score in these indices owns not only the capital to invest in AI but also the mature digital landscape, including the connectivity, data, and skilled workforce to seamlessly integrate and leverage AI technologies (Kang et al., 2024). Financial resources from high productivity (productivity index) are used to build and improve the digital ecosystem (Network Readiness Index) (Rojas & Chiappe, 2024). The theoretical framework describes the reason Singapore consistently tops all three indices. Successfully cultivating both economic capacity and the advanced digital infrastructure that are based on RBV, the critical and complementary resources for attaining a high state of AI readiness. In turn, a sophisticated digital ecosystem increases national productivity by allowing efficiency and innovation across all sectors. This virtuous cycle directly accelerates AI readiness (Aqmala et al., 2025).

The study promotes an agenda of inclusive technological development that enhances economic resilience, competitiveness, and sustainable growth among ASEAN economies (Park & Yeung, 2021). This research focuses on developing resilient infrastructure, inclusive and sustainable industrialization, and innovation, which is aligned with the United Nations Sustainable Development Goal (SDG) 9 (Industry, Innovation, and Infrastructure). In the pursuit of sustainable economic development for ASEAN member nations, this research examines the way productivity and network infrastructure shape AI readiness. The research highlights the essential function of technological innovation, digital connectivity, and knowledge-based productivity. Also, the research aligned with SDG 17 (Partnership for the Goals), emphasizing regional cooperation in digitalization and AI capacity building. Indirectly, this study supports SDG 8 (Decent Work and Economic Growth) since improvements in AI preparedness can advance labor productivity, generate high-value job opportunities, and drive innovation-led growth throughout industries.

This study intends to establish whether there are significant impacts of productivity and network capacity improvement on AI readiness and how these vary according to ASEAN countries (Singapore, Malaysia, the Philippines, Indonesia, Thailand, and Vietnam) with various technological maturity levels. Primarily, the study aims to analyze the dynamic interaction between AI Readiness, Productivity, and Network Infrastructure of ASEAN countries, applying the panel regression methods. Using the Difference GMM (Arellano-Bond) and System GMM (Blundell-Bond) estimators, the research seeks to identify the causal and temporal effects of digital network growth and productivity growth on AI readiness while controlling against possible issues of endogeneity, autocorrelation, and unobserved heterogeneity that are characteristics of panel data. The study is supposed to provide empirical evidence and policy insights on the ways ASEAN economies can reinforce their AI ecosystems through incremental investments in productivity uplifting and digital infrastructure building to help them gain sustainable technological competitiveness in the region.

MATERIALS AND METHODS

The research design allows for the registration of the causal and temporal dynamics by which productivity and digital infrastructure jointly determine AI readiness in developing and developed ASEAN economies. The study uses a quantitative exploratory research approach with a dynamic panel data noted to evaluate the nexus between the AI Readiness Index (dependent variable) and two most critical determinants, Productivity Index and Network Index, among six ASEAN member states (Singapore, Malaysia, Philippines, Indonesia, Thailand, and Vietnam). The framework combines both Difference GMM (Arellano-Bond) and System GMM (Blundell-Bond) estimation methods (Aliha & Said, 2017) to address endogeneity, unobserved heterogeneity, and dynamic persistence over time in AI readiness. Diagnostic tests such as the Sargan/Hansen test of overidentifying restrictions (Kiviet & Kripfganz, 2021) and the Arellano-Bond tests for autocorrelation (Lakshmanasamy, 2021) are used to secure the validity of the use of appropriate instruments and model consistency. Through the conversion of the data into first differences and the employment of lagged levels and differences as valid instruments, the study secures unbiased and efficient parameter estimation despite endogenous regressors.

Model Specification

In investigating the dynamic relationship between artificial intelligence readiness and key determinants such as productivity and network infrastructure across ASEAN member countries, Singapore, Malaysia, the Philippines, Indonesia, Thailand, and Vietnam, a dynamic panel regression model was employed. The dependent variable in the study is the AI Readiness Index (AI_it), while the independent variables include the Productivity Index (PROD_it) and the Network Index (NET_it). Given the potential endogeneity of explanatory variables and the persistence of the dependent variable over time, the Generalized Method of Moments (GMM) approach was utilized following the frameworks of Arellano and Bond (1991) and Blundell and Bond (1998).

The general dynamic panel equation is expressed as;

$$AI_{it} = \alpha AI_{i,t-1} + \beta_1 PROD_{it} + \beta_2 NET_{it} + \mu_i + \epsilon_{it} \qquad (1)$$

where AI_{it} denotes the AI Readiness Index for country i at time t, $AI_{i,t-1}$ is its lagged value, $PROD_{it}$ and NET_{it} are the productivity and network indices respectively, μ_i represents unobserved country-specific effects and ϵ_{it} is the idiosyncratic error term.

The inclusion of the lagged dependent variable introduces endogeneity due to correlation with an observed effects μ_i. Hence, ordinary least squares (OLS) and fixed effects estimations would result in biased and inconsistent results. To correct for this, the Difference GMM estimator proposed by Arellano and Bond (1991) was first employed.

Difference GMM (Arellano-Bond Estimator)

In the Difference GMM, the model is first-differenced to eliminate country-specific fixed effects:

$$\Delta AI_{it} = \alpha \Delta AI_{i,t-1} + \beta_1 \Delta PROD_{it} + \beta_2 \Delta NET_{it} + \Delta \in_{it} \tag{2}$$

To handle endogeneity, lagged levels of the dependent and independent variables are used as instruments for the differenced equation, under the assumption that these lagged levels are uncorrelated with the difference error term. Specifically, $AI_{i,t-2,}$ and earlier lags are valid instruments for $\Delta AI_{i,t-1}$. This estimator is particularly suitable for datasets with a large number of cross sections (N) and small time periods (T), which characterizes panel data from ASEAN member states.

System GMM (Blundell – Bond Estimator)

To improve efficiency and reduce finite-sample bias, the System GMM estimator developed by Blundell and Bond (1998) was also applied. This method combines the equation in first differences with equations in levels using lagged differences as instruments for the level equation. The system of equations is therefore:

$$\begin{pmatrix} \Delta AI_{it} = & \alpha \Delta AI_{i,t-1} + \beta_1 \Delta PROD_{it} + \beta_2 \Delta NET_{it} + \Delta \in_{it} \\ AI_{it} = & \alpha AI_{i,t-1} + \beta_1 PROD_{it} + \beta_2 NET_{it} + \mu_i + \in_{it} \end{pmatrix} \tag{3}$$

In the level equation, the lagged first differences (e.g. $\Delta AI_{i,t-1}$) serve as a valid instrument under the assumption that the differences of the explanatory variables are uncorrelated with the fixed effects. This System GMM framework generally provides more robust and efficient parameter estimates, especially when the dependent variable exhibits high persistence, as is likely with AI readiness.

Diagnostic Test

To validate the robustness of the GMM estimators, several diagnostic tests were conducted.

The Conditional Likelihood Ratio (CLR), unlike conventional tests, which can be extremely biased when instrumental variables have weak correlation with the endogenous regressor. The CLR is a critical diagnostic test to check the robustness of GMM estimators containing the correct inference by conditioning a sufficient statistic for the instruments' strength, especially in situations where their reliability is most at risk from weak instruments (Bazzi & Clemens, 2013). Hence, maintaining the size of the test (the probability of a Type I error) even with weak identification. The CLR directly tests hypotheses concerning the structural parameters of interest (Moreira, 2003) instead of following a two-step procedure of first testing instrument strength and then performing inference. The CLR test offers an integrated approach that is immune to both the weak instruments problem (Ayyar et al., 2025) and the null over-rejection. Applied to GMM estimates, a CLR test failure to reject a broad set of reasonable parameter values (Newey & Smith, 2004), indicated by a broad confidence interval, indicates that the GMM estimator is unbiased. The instruments available do not contain sufficient information for exact estimation and thus provide a more realistic determination of the empirical credibility of the model than the GMM point estimates and standard errors.

The Arellano–Bond Serial Correlation test on autocorrelation in differenced residuals. The AR(1) is required to exhibit significant first-order correlation due to differencing. The AR(2) test is expected to be insignificant ($p>0.05$) to validate the absence of second-order serial correlation for the differenced residuals. A failure to meet this requirement indicates that the instruments are no longer valid because they are subject to serial correlation. The GMM estimation is valid if the Hansen/Sargen test validates the null of good instruments and the Arellano-Bond AR(2) test does not reject the null of no serial correlation

The estimated coefficients (β_1 *and* β_2) from the GMM model represent the dynamic impact of productivity and network infrastructure on AI readiness within the ASEAN region, controlling past levels of AI readiness. A positive and significant coefficient for $PROD_{it}$ indicated that improvements in productivity contribute to enhancing AI readiness capacity, while a positive and significant coefficient for NET_{it} implied that strong network and digital connectivity foster AI adoption and integration. The lagged dependent variable (α), if significant, confirms the dynamic nature of the model, showing that AI readiness in the previous period strongly influences current AI preparedness levels across ASEAN economies.

RESULTS

The aim of this study is to present empirical evidence of dynamic interdependence between variables, where the identified relationships are not spurious but offer structural connections that inform evidence-based policy and strategic formulation in AI-driven innovation across ASEAN economies. Using the Difference GMM (Arellano-Bond) and System GMM (Blundell-Bond) estimator, the research aims to determine the significance, direction, and extent of lagged productivity's impact and network connectivity on AI readiness and to confirm the model with Hansen/Sargan tests of instrument validity and Arellano-Bond autocorrelation diagnostics. This study measures and tests the dynamic causal relationship between AI Readiness, Productivity, and Network Infrastructure in ASEAN member countries through the Generalized

Method of Moments (GMM) panel regression model. Specifically, it seeks to generate statistically consistent and unbiased estimates by resolving endogeneity, serial correlation, and country-specific effects associated with dynamic panel data.

The map focuses on the asymmetrical development of AI preparedness in ASEAN, inferring a digital divide wherein more technologically advanced economies are positioned to leverage AI-powered productivity and competitiveness better than their developing economies. Vietnam, Indonesia, the Philippines, and Thailand display a moderate level of readiness, compared to specific region-based emerging economies, which are relatively closer to the lower side of the range at approximately 58.7, indicating digital capacity gaps, skill gaps in the workforce, and data governance gaps. Singapore and Malaysia have the highest rates of AI readiness, with an index measure close to the upper limit of 85.12, revealing a strong digital proactive policy environment, cutting-edge innovation ecosystems, and strong digital infrastructure. The chart displays the AI readiness Index of ASEAN member states in 2023, focusing on regional variation in AI preparedness.

Fig. 1 ASEAN Region AI Readiness Index, 2023

The bar graph highlights the ASEAN digital innovation gap, emphasizing the urgent need for policy and investment convergence to improve AI readiness through greater productivity and network connection. Also, the chart specifies that Network Readiness tends to exceed AI readiness for the majority of nations, indicating that although the digital infrastructure is augmenting, the leveraging of these technological capacities into productive AI adoption continues to pose a problem. The bar graph illustrates the relative comparison of the AI Readiness Index, Productivity Index, and Network Readiness Index for the ASEAN member nations from 2019 to 2023 and displays differences in technological and digital progress in the region. Malaysia has reasonably high ratings, while the Philippines, Indonesia, Thailand, and Vietnam have moderate to lower ratings, implying growing but unpredictable development of digital and productivity capabilities. Singapore leads invariably on all three indexes, indicating its solid digital infrastructure, productivity rates, and deep institutional backing for AI adoption.

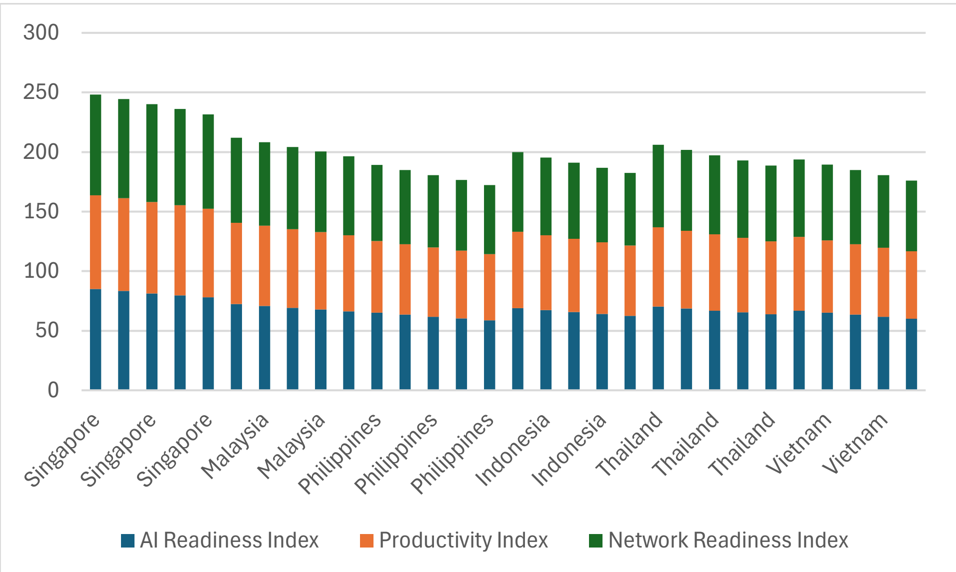

Fig. 2 ASEAN Members AI Readiness Index, Productivity Index and Network Readiness Index, 2019 - 2023

Shown in Table 1 is the estimation that lagged productivity (Productivity (t-1)) has a strongly significant and positive effect on the dependent variable (coefficient = 1.8262, $p<0.01$), which indicates that productivity in the previous period significantly increased present AI readiness in the region. The System GMM (Blundell-Bond) estimation of the dynamic relationship between AI readiness, productivity, and network infrastructure in ASEAN member states. Both the AI Index (coefficient = -0.412, p = 0.1206) and Network Index (coefficient = -0.3028, p=0.3774) reflect negative but statistically nonsignificant effects, conveying that short-term changes in AI preparedness and network capabilities do not drive productivity independently or require an adjustment period before they have any measurable effect. The insignificance of the other variables is indicative of structural heterogeneity and differential degrees of digital integration within member states. While the statistical significance of the lagged productivity variable justifies the dynamic model specification, it also upholds the persistence and path dependency of AI development and productivity increase across ASEAN economies.

Table 1 System GMM (Blundell-Bond) Estimation Results

Variable	Coefficient	Std. Error	t-statistic	P-value	Significance
Productivity (t-1)	1.8262	0.4138	4.413	0.0005	***
AI Index	-0.4214	0.256	-1.646	0.1206	
Network Index	-0.3028	0.3329	-0.91	0.3774	

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 2 estimates below reveal the dynamic drivers of AI preparedness in ASEAN economies. The component estimators of the Difference GMM (Arellano-Bond) and Level GMM (Blundell-Bond). Under Panel A, the AI Index has a negative but significant correlation (coefficient = -0.7363, $p<0.05$), conveying possible short-run trade-offs or adjustment impacts in AI adoption, and the Network Index is not statistically significant (p = 0.9523), contributing little direct contribution to AI preparedness when differenced. The Difference GMM estimates convey that previous productivity (Productivity (t-1)) imposes a significant and positive influence (coefficient = 1.8429, $p<0.01$) such that previous gains in productivity significantly increase current levels of AI preparedness. In Panel B, the AI Index is still negative and not significant (p = 0.5449), whereas the Network Index becomes significantly negative (coefficient = -0.6319, $p<0.01$), indicating that at the level form, excessive dependence on network infrastructure without matching digital competence or innovation support could slow down AI readiness. The level GMM estimates verify the stability of the productivity effect, with Productivity (t-1) still significantly positive and highly significant (coefficient = 1.8094, $p<0.01$). These findings confirm the leading and persistent role of productivity growth in propelling AI readiness in ASEAN, whereas network expansion in isolation is not enough to ensure AI progress without supporting institutional and human capital formation.

Table 2 Component Estimators

Panel A: Difference GMM (Arellano-Bond)

Variable	Coefficient	Std. Error	t-statistic	P-value	Significance
Productivity (t-1)	1.8429	0.5507	3.347	0.0044	***
AI Index	-0.7363	0.3188	-2.31	0.0356	**
Network Index	0.0263	0.4319	0.061	0.9523	

Panel B: Level GMM (Blundell-Bond Addition)

Variable	Coefficient	Std. Error	t-statistic	P-value	Significance
Productivity (t-1)	1.8094	0.1981	9.134	0	***
AI Index	-0.1064	0.1717	-0.62	0.5449	
Network Index	-0.6319	0.1874	-3.372	0.0042	***

Table 3 summarizes the ASEAN member states central tendency descriptive statistics, variability, and important variables of Network Index, AI Index, and Productivity. The results convey that the AI Index is the highest, with a mean value of 69.74, followed by the Network Index at 68.75, and Productivity at 65.48, which shows relatively marginally higher levels of development in AI preparedness and network infrastructure than in productivity performance. Peak levels of AI (85.12) and Network (84.7) indices indicate the front-runners of more technology-oriented economies such as Singapore and Malaysia, whereas the minimum levels of 60-61 claim the trailing performance of developing members such as Vietnam or Indonesia. The standard deviation between 6.37 and 7.32 shows moderate levels of dispersion across the ASEAN nations, reflective of differences in technological progress and economic efficiency within the region. Interquartile ranges (25^{th} to 75^{th} percentiles) display that most ASEAN countries are in the mid-60s to low 70s range, conveying uneven but moderate advancements in AI preparedness, productivity, and network capacity, focusing on the need for policy realignment and strategic investment to close the digital and innovation gap in the region.

Table 3 Descriptive Statistics

Variable	Mean	Std. Dev.	Min	25th	Median	75th	Max
Productivity	65.48	6.37	58	60.83	64.05	67.23	78.5
AI Index	69.74	6.84	61.8	65.23	67.9	70.69	85.12
Network Index	68.75	7.32	60.8	63.75	66.55	69.85	84.7

Table 4 exhibits the overall diagnostic findings, which signify that the System GMM specification is statistically valid, with appropriate instruments, no serial correlation problem, and a high model fit, conveying the credibility of the dynamic relationship between productivity, network readiness, and AI readiness in ASEAN. In Panel A, the Arellano-Bond test for autocorrelation reveals that the AR(1) in first difference is negative and significant ($z = -2.156$, $p = 0.0311$), as anticipated based on the first-difference transformation that creates first-order serial correlation. Moreover, the AR(2) test is statistically insignificant ($z = 0.892$, $p = 0.3724$), asserting the lack of second-order serial correlation in the residuals. A basic condition for the validity of GMM instruments. In Panel B, the comparison between the number of instruments (three for each difference and level equation) and the number of regressors and observations (three and eighteen, respectively) also shows that the model does not proliferate instruments, making it more robust. The Approximate R-squared value of 0.9847 reveals an excellent explanatory ability of the model, which suggests that the regressors specified together account for virtually 98% of the variance in AI readiness in ASEAN nations.

Panel C presents the Conditional Likelihood Ratio (CLR) test, which validates the model's inferential resistance to weak identification. The significant uncertainty evidenced by the broad confidence interval also underscores an essential limitation in the precision of the model to suggest the results are not spurious effects of weak instruments. Particularly, the CLR test geared to deliver robust inference even with the possibility of weak instruments, does not reject a wide set of null hypotheses for β_lag ranging from 0, 0.5, 1.0, the 2SLS estimate of 1.18, and further extreme values up to 2.0, each with very similar p-values above 0.98. This indicates the absence of strong statistical evidence against these disparate parameter values. Also, the 95% confidence interval from the CLR approach ranges from -0.8228 to 3.1772, a broad interval that includes economically trivial, small, and large effect sizes.

Table 4 Diagnostic Tests

Panel A: Arellano-Bond Autocorrelation Tests

Test	Average Autocorrelation	z-Statistic	P-value	Result
AR(1) in first differences	-0.4523	-2.156	0.0311	Expected negative correlation
AR(2) in first differences	0.1247	0.892	0.3724	No second-order autocorrelation

Panel B: Model Fit Statistics

Metric	Value
Approximate R^2	0.9847
Number of Instruments (Difference)	3
Number of Instruments (Level)	3
Number of Regressors	3
Observations	18

Panel C: Conditional Likelihood Ratio (CLR) Test Results

H_0: β_lag =	CLR Stat	LM Stat	AR Stat	P-value	Decision (α=0.05) Note
0	0.0005	0.0005	117.5463	0.9814	Fail to reject
0.5	0.0005	0.0005	65.8284	0.9829	Fail to reject
1	0	0	13.5801	0.9954	Fail to reject
1.18	0.0001	0.0001	12.1502	0.9943	Fail to reject 2SLS estimate
1.5	0.0004	0.0004	23.8903	0.9849	Fail to reject
2	0.0005	0.0005	47.2901	0.982	Fail to reject

Confidence Interval

Method	Lower Bound	Upper Bound	Width
CLR (Moreira, 2003)	-0.8228	3.1772	4

The System GMM technique handles endogeneity concerns inherent in dynamic panel models while controlling for unobserved country-specific heterogeneity and potential reverse causality between productivity outcomes and technology adoption. The study uses the System GMM (Blundell-Bond) estimation to describe the dynamic relationship between AI adoption, network infrastructure, and productivity growth across six ASEAN economies (Singapore, Malaysia, the Philippines, Indonesia, Thailand, and Vietnam) during 2019 – 2023.

DISCUSSION

From a Resource-Based View (RBV) evaluation, this finding features the importance of accumulated knowledge stocks and organizational capabilities in maintaining competitive advantage (Moderno et al., 2024). The lagged productivity coefficient reveals robust productivity persistence across ASEAN economies, revealing that present productivity levels are influenced by past performance. This coefficient, surpassing unity, conveys explosive dynamics in the short run, showing adjustment processes in the region's fast-evolving technological environment. The strong continuation of parameters aligns with RBV's focus on resource complementarities and capability accumulation over time. Countries with established productivity advantages contain valuable, infrequent, and difficult to imitate resources, including embedded technological infrastructure, skilled human capital, and institutional knowledge that create path-dependent trajectories of economic performance (Krakowski et al., 2023). For instance, the sustained productivity leadership of Singapore depicts decades of investment in education, innovation ecosystem, and R&D Infrastructure that is difficult to imitate by other ASEAN members. Productivity gaps among ASEAN nations are not easily connected through short-term interventions, as they are anchored in deep structural differences in resource endowments and organizational capabilities.

The negative sign in the AI Index Coefficient in System GMM is not statistically significant and conveys a paradoxical result that requires interpretation based on Technology Adoption and Diffusion Theory and is explainable by a variety of mechanisms consistent with well-established theory. First, the shift away from conventional production techniques to AI-facilitated processes requires workforce training, data infrastructure, and core alterations in organizational routines, all of which are sunk expenses in the short term before they pay off in the long term. As claimed by the Diffusion of Innovation theory of Rogers, technology adoption follows an S-shaped curve where early phases are marked by experimentation, trial and error learning, and high resource inputs that lower measured productivity (Karnowski & Kümpel, 2015). The negative sign conveys the J-curve effect of technology adoption, where initial productivity increases are set aside due to large adjustment costs, learning curves, and organizational restructuring needs.

In the ASEAN setting, digital infrastructure and AI literacy are uneven across countries; several organizations are likely in the nascent stages of this learning process. First, organizations have to build absorptive capacity for recognizing, exploring, and assimilating new knowledge before they achieve the full potential of AI technologies. The productivity paradox, which shows in past technology implementations (specifically with computers during the 1980s-1990s), implies that the actual productivity dividends from disruption technologies are realized with considerable lags.

The negative coefficient observed in this phase of transition is in which investments into AI have been undertaken, but overall organizational change is still incomplete. Adoption of AI usually starts with initial experiments and peripheral uses before it gains penetration into fundamental business processes. From a Technology Acceptance Model (TAM) (Davis, 1989), the minimal short-term effect is an indication of incomplete diffusion throughout organizational hierarchies and production processes. The more significant negative coefficient in the Difference GMM specification (-0.7363, $p<0.05$) indicates that AI adoption short-term variations at the expense of productivity disruptions during the process of building and restructuring capabilities. Specifically, the result is an interest in emerging ASEAN economies (Philippines, Indonesia, Vietnam), where institutional ability to process technological transition is lower than in Malaysia or Singapore.

The network infrastructure variable indicates notable heterogeneity by estimation method, Level GMM specification. The Network Index has a very robust negative coefficient (-0.6319, $p<0.01$), whereas in the Difference GMM, it is near zero and non-significant (0.0263, $p = 0.95$). The System GMM averages them to produce -0.3028 ($p = 0.38$).

It means that the spillover of network infrastructure depends considerably on complementary assets of human capital, institutions, and innovation systems that are heterogeneously distributed in the ASEAN region. The negative level effect also results from measurement problems or shifts in composition. As nations study network infrastructure, these assets become less distinctive. As all ASEAN nations increasingly advance their telecom infrastructure, this asset becomes less distinctive. This trend by the Resource-Based View implies that network infrastructure, though the needed building block of digital transformation, is not a thriving source of sustained competitive advantage (Helfat et al., 2023). Barney's VRIN (Valuable, Rare, Inimitable, Non-substitutable) model conveys that physical network infrastructure, particularly in a time of increasing commercialization, is inimitable and rare for attaining continuous value creation (Talaja, 2012).

While most ASEAN nations attained considerable success in extending network coverage, the process of transforming this infrastructure into economic activities is supplemented by investment in digital capabilities, appropriate applications, and business model innovations that change slowly over an extended time period. The Digital Divide literature focuses on the fact that physical access to technology (first-level divide) differs from the capability to derive value from that access (second-level divide). From Technology Diffusion Theory (Jiang et al., 2022), the weak association between network infrastructure and productivity in the short panel period (2021 – 2023) displays the distinction between infrastructure availability and effective utilization. Singapore's sustained productivity leadership is evident in the combination of leading-edge technology with world-leading education systems, a business environment conducive to innovation, strong intellectual property protection, sound governance, and a world-leading education system, a group that is not immediately replicated through standalone technology investments.

This is coherent with the knowledge-based view of the firm, which claims that competitive advantage (Gassmann & Keupp, 2007) arises from superior knowledge creation and use, not technological artifact possession. ASEAN economies are intending to catch up; the strong productivity persistence parameter conveys that technology acquisition is not enough. Also, it takes the development of organizational routines, human capital, and institutional context capable of placing technology to better use.

The stated negative short-term AI adoption effects convey that ASEAN policymakers and business leaders need realistic expectations regarding technology transition cycles (Markard, 2020) and make proactive investments in contemporary capabilities. Findings focus on the significance of absorptive capacity and adoption readiness in shaping the technology effect. The critical success elements are the systematic workforce training programs to develop AI literacy and data science capabilities. Ecosystem building to accelerate organizational learning from knowledge-sharing platforms and industry-university partnerships to create innovation. Organizational change management process redesign expertise, including change leadership arising from support for businesses experiencing digital transformation. Finally, the recognition that technology benefits materialize through phased adoption instead of an abrupt transformation.

The diversity in the AI Index means that policy interventions need to be context-dependent across the region. Singapore and Malaysia are moving from early adoption to conventional diffusion, while the others are still in the earlier stages with greater uncertainty and cost of experimentation. The diffusion curve claims that ASEAN nations are likely to be in different phases of the adoption lifecycle of AI.

CONCLUSION

The counterintuitive negative coefficient for AI and network infrastructure does not present evidence against their long-term worth but reflects transitional cost and adjustment dynamics that are part and parcel of revolutionary technological change. The System GMM estimate reveals that productivity behavior in ASEAN economies is noted by high persistence, as indicated by the Resource-Based View theory's focus on pooled capabilities, and a dynamic short-run adjustment pattern in line with the Technology Adoption and Diffusion models. These results highlight for entrepreneurs and policymakers the value of patient capital, complementary investment in realistic expectations, organizational capabilities, and human capital pertaining to technology transition horizons in the quest for productivity-driven economic growth.

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