Research on World Agricultural Economy
https://journals.nasspublishing.com/index.php/rwae

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Stage-Dependent Dynamics of the Digital Economy, Agricultural Innovation, and Growth in Asia-Pacific Economies

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ABSTRACT

Digital development is transforming agriculture; however, the relationship between the digital economy, technological innovation and economic growth varies significantly across stages of national development. The present study proposes a tripartite "Digital–Innovation–Growth" framework to investigate and understand its mechanism of operations. To achieve this, data from 15 Asia-Pacific economies for the period spanning 2000 to 2021 are used through a Panel Vector Autoregression (PVAR) model. This framework operates through a tripartite mechanism: First, digital infrastructure lowers information and transaction costs, which in turn helps in adopting new types of agricultural technological innovation. Secondly, innovation enhances agricultural productivity through total factor productivity enhancements. Finally, agricultural growth generates demand and surplus capital, thereby stimulating further digital investment and application. Distinct stage-dependent patterns emerge in the analysis. The results of the Granger causality tests indicate that agricultural economic growth is a significant driver of digital development. The heterogeneity analysis shows three regimes: one for the developed economies with a bi-directional reinforcement mechanism; growth-driven digitalization in emerging economies and weak systemic linkages in developing economies. The findings confirm the proposed stage-dependent framework and provide a basis for analyzing dif-

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ARTICLE INFO
Received: 29 September 2025 | Revised: 20 November 2025 | Accepted: 25 November 2025 | Published Online: 26 May 2026
DOI: https://doi.org/10.36956/rwae.v7i2.2796

CITATION
Tang, Z., 2026. Stage-Dependent Dynamics of the Digital Economy, Agricultural Innovation, and Growth in Asia-Pacific Economies. Research on World Agricultural Economy. 7(2): 581–596. DOI: https://doi.org/10.36956/rwae.v7i2.2796

ferentiated policy interventions to reduce the agricultural digital divide.

Keywords: PVAR Model; Digital Economy Composite Index; Agricultural Technological Innovation; Agricultural Economic Growth; Heterogeneity Analysis; Asia-Pacific Economies

1. Introduction

Agriculture continues to be a core sector of economic activity and employment in the Asia-Pacific region, especially in developing economies, where it is key to food security and rural livelihoods [1, 2]. Simultaneously, the region has undergone rapid digital transformation, characterized by continuous improvements in digital infrastructure and services [3–5]. However, the benefits of digital expansion have been limited and unevenly distributed, with persistent disparities linked to countries' developmental status. These divergent developmental characteristics underscore the importance of studying the relationship between the digital economy, innovation in agricultural technology and agricultural economic growth. Agricultural economic growth, in this study, is defined as the increase in scale and productivity of the agricultural sector, measured by the log of agriculture, forestry and fishery value added (constant 2015 USD) in accordance with international measurement practices [1, 2, 6].

Previous research has extensively examined the digital economy as well as agricultural innovation. Yet, very few studies bring all three dimensions together in one analytical framework [7, 8]. A study from China shows that the digital economy reduces transaction costs in agricultural modernization and improves resource allocation efficiency and total factor productivity. Digital finance and rural e-commerce help farmers access new markets and earn a higher income. Agricultural technological innovation encompasses spending on research and development, technology importation and use, as well as the spillover of expertise. The literature seldom examines how these digital-agriculture linkages evolve with economic development. The significance of these developmental disparities across growth stages is self-evident. The Asia-Pacific region, where economies occupy all levels of development, constitutes a natural laboratory for analysis of stage-dependent dynamics.

According to worldwide research, digital technologies can increase market access for smallholders by lowering information asymmetry [9–11]. Through agricultural e-commerce and branding on social media, farmers are able to make an impact at local and global levels. It demonstrates the role of community-supported agriculture (CSA), which has become supplementary to farmers' income [12]. However, most existing research focuses either on single countries or one-dimensional mechanisms, relying largely on static panel models that cannot capture dynamic interactions or feedback effects. Few studies explicitly analyze structural differences across development stages or investigate nonlinear, heterogeneous relationships among digitalization, innovation, and agricultural growth.

To address these gaps, this study develops a unified "Digital–Innovation–Growth" analytical framework and introduces the concept of stage-dependent interaction. This concept posits that the relationships among digitalization, innovation, and agricultural growth evolve systematically with a country's level of development, challenging the "one-size-fits-all" assumption in existing literature. To empirically test these dynamic linkages, a Panel Vector Autoregression (PVAR) model [13] is employed. In addition, a Digital Economy Composite Index is developed to more accurately reflect cross-country variation in digital development.

The theoretical basis of the study draws on three strands of literature: Endogenous Growth Theory, the National Innovation Systems (NIS) framework, and Digital Economics. According to Endogenous Growth Theory, innovation and knowledge accumulation are significant contributors to long-term growth. Agricultural patent applications can be a good measure of innovation, as discussed in this paper. The NIS theory deals with institutions, regulation and linkages among firms which affect national innovation capabilities. The impact of technological change on lowering search and transaction costs, speeding up the flow of information and enabling the development of new business models constitutes digital economics. Thus, together, the innovation system and co-evolution theories offer a multi-layered understanding of how digitalization, innovation and agricultural growth co-evolve across various development stages, thereby offering the conceptual basis for the stage-dependent framework.

A limitation of generalizability is that the 15 Asia-Pacific economies may constrain generalizability. Data limitations persist, especially regarding digital industrial integration and disaggregated agricultural patents. Future studies could involve micro-survey datasets or more structural indicators. When a PVAR model is estimated, then the dynamic interaction between shocks and endogenous variables is captured. However, the PVAR estimation does not necessarily identify transmission channels. Mediation models or structural approaches may be needed for this.

In spite of these limitations, the Asia-Pacific region has the right conditions to test the stage-dependent framework because of the differences in economic structure, institutional capabilities, and technological maturity. The diversity in question, along with the region's focus on food security and digital transformation, makes the research policy relevant. The goal of these findings is to support evidence-based contextual policymaking for enhancing digitalization and innovation in agriculture.

The following hypotheses are proposed based on the conceptual framework:

H1. *There is a strong complementarity effect between digital economy and agricultural technological innovation*.

H2. *Economic growth in agriculture has positive feedback on the development of the digital economy and investment in technology innovation*.

H3. *The dissimilarity in economic development stages leads to diversity in structural relatedness of digitalization, innovation and agricultural economic growth*.

The remainder of the paper is structured as follows. Section 2 presents the methodological framework and data. Section 3 reports the empirical results. Section 4 will present an analysis of heterogeneity and robustness tests. The conclusion within Section 5 includes policy recommendations and future research directions.

2. Research Design and Data

2.1. Model Specification

To jointly estimate the dynamic interdependencies among agricultural economic growth, agricultural technological innovation and the digital economy, a Panel Vector Autoregression (PVAR) model is used following Holtz-Eakin et al.[14]. This study employs a Panel VAR (PVAR) specification for the analysis:

$$Y_{it} = \mathit{\Gamma}_0 + \sum_{p=1}^{k} \mathit{\Gamma}_p Y_{i,t-p} + \mu_i + \varepsilon_{it}$$

where is a vector of endogenous variables comprising the logarithm of agricultural value added (*lnAgricult*), the logarithm of agricultural patent applications (*lnPatent*), and the Digital Economy Composite Index (*Digital*). $\mathit{\Gamma}_p$ denotes the coefficient matrices for the *p*-th lag, captures country-specific fixed effects, and is the idiosyncratic error term.

The choice of PVAR over univariate dynamic panel approaches (e.g., Difference GMM or System GMM) is motivated by both theoretical and methodological considerations.

Initially, the core hypotheses of the study state that feedback loops and bidirectional causality necessitate a modelling strategy within which all variables must be treated as endogenous. Second, PVAR impulse response functions (IRFs) enable tracing cross-period transmission paths and forecast error variance decomposition (FEVD) enables the measurement of the different shocks. Thus, they provide richer insights into "stage-dependent dynamics" than single-equation models. The third step involves estimation using the Generalized Method of Moments (GMM), a method particularly appropriate for short panels. GMM helps reduce endogeneity bias. Moreover, by incorporating time effects and unit-specific heterogeneity, it mitigates omitted variable risks and thereby strengthens causal interpretation.

The empirical sample is composed of 15 Asia-Pacific economies with World Bank classifications into developed, emerging and developing economies as measured by their agricultural structure and digitalization as indicated in **Table 1**. These classifications remained constant throughout the study period.

Table 1. Classification of Sample Economies.

Development Stage	Economies Included
Developed Economies	Japan, South Korea, Singapore, Australia, New Zealand
Emerging Economies	China, India, Indonesia, Malaysia, Thailand, Vietnam, Philippines
Developing Economies	Pakistan, Bangladesh, Sri Lanka

Source: Author's classification based on World Bank data.

The process of selecting the 15 economies involves a systematic multi-step screening process that ensures analytical coherence and comparability across economies.

Economic Development Classification. Countries were only included in the analysis if the income group of the countries remained the same during 2000–2021. This ensures the validity of stage-dependent heterogeneity analysis.

Agricultural Sector Significance. This study retains only those economies in which agriculture plays a structurally relevant role, defined as meeting at least one of the following criteria: (i) the agricultural sector accounts for at least 5% of total employment, (ii) it exhibits a high share of agricultural value added, or (iii) it demonstrates strategic investments in agricultural innovation (e.g., Japan's agricultural robotics and Korea's smart-farming technologies).

Digitalization-Relevant Infrastructure and Data Availability. Inclusion required a complete data series for mobile and broadband penetration, all ICT infrastructure indicators, secure-server density, agricultural patents, and agricultural value added.

The above criteria ensure that the digital innovation growth variables are comparable both cross-sectionally and longitudinally, providing a methodologically robust sample for PVAR estimation.

The classification of economies into developing, emerging and developed stages follows three quantitative thresholds as per operational transparency to ensure consistent application throughout the sample period:

The entropy-weighted Digital Economy measures the digitalization threshold (D):

Developing: $\mathbf{D < 0.30}$

Emerging: $\mathbf{0.30 \leq D < 0.70}$

Developed: $\mathbf{D \geq 0.70}$

Innovation capability threshold (I): measured by agricultural resident-filed patent applications

Developing: $\mathbf{I < 200}$ **patents/year**

Emerging: $\mathbf{200 \leq I < 3000}$ **patents/year**

Developed: $\mathbf{I \geq 3000}$ **patents/year**

Agricultural structural threshold (A): based on agricultural value added (constant 2015 USD)

Developing: $\mathbf{A < 5 \times 10^{10}}$ **USD**

Emerging: $\mathbf{5 \times 10^{10} \leq A < 2 \times 10^{11}}$ **USD**

Developed: $\mathbf{A \geq 2 \times 10^{11}}$ **USD**

An economy will be allotted to a stage only if a minimum of two of the three quantitative criteria are satisfied consistently over the period 2000–2021. The hybrid approach, which includes the income categories, the digitalization data and the innovation metric, is in line with multi-dimensional frameworks of development and increases stage-dependent analysis's empirical precision [15, 16].

2.2. Variable Selection and Data Sources

The Digital Economy Composite Index (*Digital*) is constructed along three dimensions: digital infrastructure, digital application, and industrial digital integration. Indicators include mobile cellular subscriptions, internet-user penetration, fixed-broadband subscriptions, and secure-server density. Data originate from ITU, the World Bank, and national statistical agencies. All indicators are normalised using min–max scaling, and objective weights are determined through the entropy method, which rewards indicators with greater discriminatory power across countries and time [17, 18].

To enhance robustness, data were first checked for missing observations and, where necessary, linearly interpolated. After normalisation, the entropy method was applied to compute the contribution of each indicator to cross-sectional and temporal variation. The composite index for each country-year is the weighted sum of its indicators.

For evaluation, PCA results were also used to formulate a different digital-economy index. There is a strong correlation between the PCA-based index and the entropy-weighted index, which confirms that this measure is not sensitive to the weighting method.

Agricultural Technological Innovation (*lnPatent*): Agricultural innovation is captured by the logarithm of resident-filed agricultural patent applications, sourced from WIPO. Applications are preferred over grants due to their timeliness and sensitivity to innovation cycles [19, 20]. Only domestic-applicant patents are retained to reflect local technological capacity.

Agricultural Economic Growth (*lnAgri*): Agricultural economic growth is proxied by the logarithm of agricultural, forestry, and fishery value added (constant 2015 USD), sourced from the World Bank's World Development Indicators [1, 2, 6].

To confirm robustness, the logarithmic transformation of the Digital Economy Index—*ln(Digital)*—was constructed. The Pearson correlation between the original series and its log transformation is 0.85, while the Spearman rank correlation between the original index and its within-year rankings is 0.82. These results indicate that both the absolute level and relative ordering of economies are highly stable, confirming the internal consistency of the digitalization measure.

2.3. Data Processing and Model Testing

Panel unit-root tests (LLC and IPS) [21, 22] were applied to all logarithmic variables (*lnAgricult*, *lnPatent*, *lnDigital*). The results show non-stationarity in levels but stationarity in first differences (**Table 2**), satisfying the requirements for PVAR estimation.

Lag length was determined using AIC, BIC, and HQIC, all of which converged on a lag order of two (**Table 3**). The eigenvalues of the characteristic polynomial lie inside the unit circle, supporting and validating the PVAR(2) specification.

Although the PVAR model estimated using the GMM estimator and lagged regressors mitigates endogeneity concerns, there are certain sources of bias that one should be careful about. The main limitations are simultaneous causality: while the use of lags reduces this risk, we cannot rule out the possibility that unobserved shocks affect all variables at the same time; and omitted variable bias: while country-fixed effects deal with time-invariant unobserved heterogeneity, time-variant unobserved factors not included in the model could still affect the results.

Table 2. Panel Unit Root Tests (First Differences).

Variable	LLC Statistic	*P*-Value	IPS Statistic	*P*-Value	Conclusion
d.lnAgricult	−13.688	0.000	−8.143	0.000	Stationary
d.lnPatent	−15.127	0.000	−9.596	0.000	Stationary
d.InDigital	−11.978	0.000	−5.664	0.000	Stationary

Source: Author's calculations using Stata 18.

Table 3. Lag Order Selection Criteria.

Lag	AIC	BIC	HQIC
1	−4.256	−3.547	−3.965
2	−5.118	−4.102*	−4.687*
3	−5.024	−3.701	−4.453

Note: * indicates the selected lag order based on the respective criterion.
Source: Author's calculations based on Stata 18.

In addition to the core estimation method, this article employs several strategies to bolster the findings against these endogeneity concerns. First, the inclusion of country-fixed effects absorbs time-invariant heterogeneity across economies. Second, the dynamic structure of the model, which treats all variables as endogenous, inherently accounts for feedback effects. The consistency of the core results across robustness checks—using alternative proxies for the digital economy and varying the sample period—provides further assurance that the identified stage-dependent dynamics are not merely endogeneity artefacts.

2.4. A Stage-Dependent Theoretical Framework

This study brings together Endogenous Growth Theory, National Innovation Systems (NIS) theory, and Digital Economics to develop a conceptual framework through which we can understand how digitalization, innovation, and agricultural growth evolve together as a country develops. The linkage between the three is neither linear nor random. Rather, it is influenced by the interaction between demand-pull forces, which are induced by agricultural growth, and supply-push forces, which occur due to the maturity of the innovation system.

The foundation establishment stage for developing economies usually has weak innovation systems, with a low level of human capital, institutions, and complementary assets. Thus, the low level of absorptive capacity makes it impossible to transform digital technology into technological innovations. The growth of agriculture is dependent on traditional factor inputs. Thus, linkages with digitalization and innovation are weak.

During the transformation-driven stage, agricultural growth generates significant market demand, capital accumulation and efficiency pressures, providing emerging economies with strong demand-pull effects. Agricultural supply chains are seeing the use of digital technologies, but innovation systems are only partly responsive. A lot of technology work consists of adopting research and borrowed technology. The crowding-out effect is empirical and short-term due to demand-driven and structurally unbalanced evolution.

In the advanced economies of the synergistic integration stage, agriculture-related demand-pull forces and mature innovation systems' supply-push forces reinforce each other. Advanced digital technologies—such as AI, the Internet of Things (IoT), and big data—are embedded not only in production but also in the R&D process itself. Moreover, the exploration of these advanced technologies leads to frontier innovation. The innovation of digital technology broadens the scope of applications in the digital economy, leading to a virtuous cycle consistent with endogenous growth.

The subsequent stage will be achieved gradually with the building up of specific structural and institutional capacities. This essay will provide an overview of the problem, definitions of various concepts, an analysis of development-path theory as it relates to structural transformation, the role of institutions, human capital and innovation capability, and digital absorptive capacity, and finally finish with a conclude. Drawing on development-path theories and structural transformation literature, in particular insights on institutional thresholds and in particular the middle-income trap [23–25], I put forward the argument that an economy will move from one stage to the next after crossing critical thresholds in three core dimensions: institutional maturity (e.g., effective governance, IPR enforcement), human capital and innovation capability (e.g., educated labour force, R&D expenditure), and digital absorptive capacity (e.g., ubiquitous infrastructure, digital skills). At the beginning, low amounts of these assets mean digital inputs cannot be effectively translated into innovation outputs. As an economy develops these capabilities, usually due to demand-pull from agricultural changes and selective policy measures, it reaches a threshold. The economy enters a new juncture of digital-innovative-growth resource coupling owing to a structural shift, where supply-push forces from a mature innovation system start to cooperate with demand-pull forces. The measurable thresholds for digitalisation, innovation and the agricultural structure in Section 2.1 (which all serve as underlying drivers) operationalise this stage transition concept.

As a result of these findings, a framework is developed which explains the heterogeneous empirical results and serves as a diagnostic tool for policymakers. While economies do not necessarily progress in a strictly linear sequence, the framework helps identify the structural constraints and policy levers that are necessary for transitions.

Under the proposed framework, the transition of stages is not haphazard and can be traced back to specific structural mechanisms that emerge from the maturity of the institution, its capacity to innovate and its digital absorptive capacity. According to the theories, that is, development-path theories and structural transformation literature[23–25], a transition occurs when an economy accumulates the appropriate technological and institutional assets to convert digital inputs into tangible innovation outputs. In the early stages, the deployment of digital tools is limited due to low absorptive capacity, weak coordination among institutions and low capital formation. As economies enter the phase of transformation, the demand-pull forces at work here are driven by rising agricultural incomes. At the same time, the gradual improvement in governance, financial markets, and human capital can permit the partial use of digital technology. The move to the synergy stage requires mature innovation systems, coordinated national innovation strategies and strong intellectual property enforcement. These conditions enable supply-push and demand-pull mechanisms to reinforce each other. The stage position of each economy and the likelihood and direction of upward transition are determined by these structural thresholds.

To enhance the internal coherence of the framework,as illustrated in **Figure 1**, linkages can be operationalized through measurable channels linking digitalization to innovation outcomes, and innovation to agriculture outcomes. Digital technologies lower the costs of search, coordination, and monitoring. These costs can be measured through proxies such as secure-server density, broadband penetration, or the ITU digital development index[11]. The reduction in information and transaction costs fosters agricultural R&D and experimentation, which is reflected in increased patent applications. This technological progress is subsequently translated into productivity gains, as measured by total factor productivity (TFP) growth-accounting methods—a well-established relationship in the agricultural economics literature[26, 27]. Finally, the resulting agricultural growth generates demand for advanced digital services, evidenced by the adoption of mobile money, the growth of rural e-commerce, and the increasing use of agricultural ICT applications.

As a whole, these quantifiable mechanisms ensure that the conceptual model is not just a layered theory but a coherent causal system linking digitalization, innovation and agricultural growth.

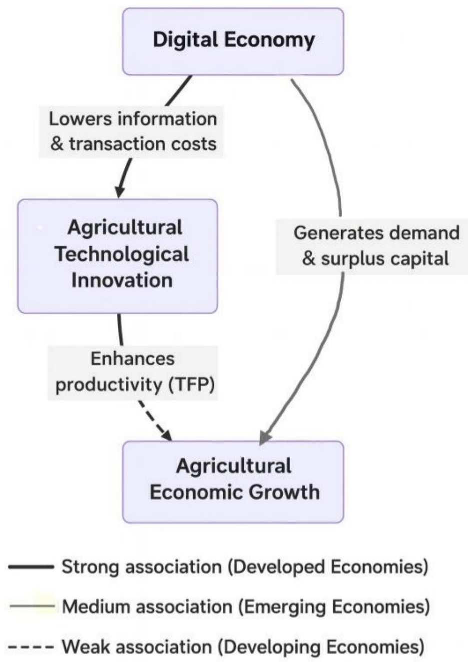

Figure 1. Conceptual Framework of the Stage-Dependent "Digital–Innovation–Growth" Nexus.

Source: Author's creation.

3. Empirical Results and Analysis

Using the full sample of 15 Asia-Pacific economies for 2000–2021, clear stage-dependent patterns emerge in the evolution of digitalization, innovation, and agricultural output. In 2000, the average Digital Economy Index was around 41 in developed economies, 4.4 in emerging economies, and roughly 0.3 in developing economies. By 2021, these averages had climbed to 94.1, 73.3, and 34.9, respectively

A similarly widening gap appears in agricultural innovation. At the start of the period, developed economies recorded about 115,000 agricultural patent applications on average, compared with roughly 11,500 in emerging economies and fewer than 1,000 in developing economies. By 2021, countries in the emerging economies group had increased their patent count to over 241 thousand, which is more than double their 2000 level. In contrast, the ones in the developing economies group only managed to reach around 0.7 thousand. The agricultural value added also increased among all groups. In all, the sectoral output for the whole economy increased, most prominently in the emerging economies group from about (2000) 1.27×10^{11} USD to (2021) 2.73×10^{11} USD. Overall, progress was made but the biggest challenge reported remained structural transformation.

Digitalization and innovation evolution patterns confirm that the developed and emerging economies have advanced the most. In contrast, the developing economies are still suffering from major digital and innovation gaps. This aligns with the stage-dependent dynamics highlighted in the PVAR analysis.

3.1. Full-Sample Estimation Results

Table 4 shows the estimated coefficients from the PVAR(2) model. Several key findings emerge. To begin with, the digital economy exhibits strong path dependence, as evidenced by the first lag of *lnDigital* being positive and significantly different from zero. Furthermore, the second lag partially offsets this effect, indicating dynamic adjustment and not explosive growth. Further, lagged coefficients in the *lnDigital* equation suggest that agricultural growth has a significantly negative short run impact on the digital economy. Third, agricultural innovation (*lnPatent*) is driven by its own past values, while agricultural growth and digitalization do not have any statistically significant short-run effects.

The findings indicate that short-run growth in the agricultural sector can divert resources away from digitalization. This may be a mechanism of "adjustment-cost" when structural change occurs. In an agricultural boom, funds are directed to conventional assets, thus the incentive to invest in digital technology may weaken for a temporary period. Additionally, market funds are channeled into conventional assets such as land, machinery, fertilizer, and working capital. The significant impact of the digital economy's own lags may indicate that network externalities are present in digital infrastructure. There are also solutions involving cumulative processes. R&D and knowledge accumulation can also be involved. The lack of any immediate cross-effects on innovation is consistent with the long and often uncertain nature of R&D from investment to patentable inventions and then the measurable impact on the economy.

Table 4. PVAR (2) Model Estimation Results.

	d ln Agriculture Equation		**d ln Patent Equation**		**d ln Digital Equation**	
	Coefficient	***p*-Value**	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**
d.L1.lnAgriculture	−0.063	0.604	−0.130	0.829	−0.802***	0.013
d.L2.lnAgriculture	−0.063	0.470	0.298	0.641	−0.051	0.891
d.L1.lnPaten	0.010	0.140	−0.252***	0.016	0.069	0.384
d.L2. lnPaten	0.001	0.883	−0.088	0.309	−0.022	0.641
d.L1.lnDigital	0.005	0.664	0.106	0.577	0.588***	0.000
d.L2.lnDigital	−0.008	0.492	0.169	0.178	−0.291***	0.000
goodness of fit	2.45e-33					

Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.
Source: Author's calculations based on Stata 18.

Theories on resource-allocation and structural transformation can be employed to explain agricultural growth's short-term negative effects on digitalization. As conventional farm output rises quickly, money and management resources are shifted to conventional production assets such as land, fertilizer, machinery and labor, and away from intangible investment such as digital technology or ICT-enabled services. According to development literature, periods of rapid expansion of a specific sector tend to crowd out modernization investments. The major reasons are liquidity constraints, risk aversion and a rigid institutional environment [28, 29]. Moreover, in emerging countries with low levels of digital absorptive capacity, rapid output growth results in strong short-run operational pressures, increasing the cost of adoption of digital systems that require training, complementary skills, and time to adjust. The negative short-run coefficient is not anomalous. It corresponds with something that the economist would label "adjustment-cost effects." Adjustment-cost effects are predictable and, in this case, occur during the agricultural upgrading process. Later, these adjustment-cost effects reverse as the pressures towards modernization accumulate.

3.2. Granger Causality Tests

Panel Granger causality tests shed more light on the direction of influence among the three variables (**Table 5**). The results show that agricultural growth is a statistically significant Granger cause of digital development. In this regard, agricultural growth is confirmed as a contextual factor causing digital growth. In the short run, neither agricultural growth nor digitalization appears to significantly Granger-cause innovation, as such innovation usually occurs in a gradual way.

Overall, these results strengthen the full-sample PVAR results. While agricultural growth has a short-term negative impact on digitalization, it also creates a demand foundation for it in the longer term. Moreover, innovation typically operates on a longer time horizon than these short-term adjustments.

Table 5. Granger Causality Test Results.

Null Hypothesis	X^2	*P*-Value	Conclusion
d.InPatent is not the cause of d.InAgriculture	2.432	0.296	Accept the null hypothesis
d.lnDigital is not the cause of d.lnAgriculture	1.497	0.473	Accept the null hypothesis
Neither d. lnPatent nor d. ln Digital is the cause of d. ln Agriculture	6.619	0.157	Accept the null hypothesis
d.InAgriculture is not the cause of d. ln Patent.	0.496	0.780	Accept the null hypothesis
d.lnDigital is not the cause of d.lnPatent.	2.450	0.294	Accept the null hypothesis
Neither d.lnAgriculture nor d.lnDigital is the cause of d.lnPatent.	3.164	0.531	Accept the null hypothesis
d.lnAgriculture is not the cause of d.InDigital.	7.411	0.025	Reject the null hypothesis. **
d.InDigital is not the cause of d.lnPatent.	1.882	0.390	Accept the null hypothesis
Neither d.lnAgriculture nor d.lnPatent is the cause of d.lnDigital.	8.193	0.085	Reject the null hypothesis. *

Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.
Source: Author's calculations based on Stata 18.

3.3. Impulse Response Analysis

The impulse response functions, shown in **Figure 2**, are presented over a ten-period horizon to visualize the effect of shocks on each of the variables. Three key patterns can be summarized.

- A positive but temporary response of innovation following a digital shock, indicating that digitalization fosters agricultural innovation in the short-to medium-run.
- A negative initial response of the digital economy to an agricultural growth shock, followed by a rebound, is consistent with the short-run adjustment-cost interpretation.
- Most responses dissipate within five to six periods, suggesting that the main dynamic linkages operate primarily in the short to medium term.

The impulse response analysis provides a time-phased perspective that complements the coefficient estimates. After digital shocks, innovations see a temporary rise. This is because digital tools reduce experimentation barriers. These tools give companies access to open data and simulations. Open collaboration also generates new patentable ideas. Although performance initially improves after systems become plug-and-play compatible, such gains do not persist without sustained investment and integration. The V-shaped response of the digital economy to an agricultural-growth shock indicates a dynamic adjustment path. This consists of a slowdown likely caused by competition for resources and then a recovery. Next, it shows a positive pull as incomes rise and modernisation pressures boost demand for digital solutions. These effects last for only about 5–6 years; therefore, long-term co-evolution requires sustained investment and policy support, especially in economies not yet at the synergistic stage.

3.4. Variance Decomposition

The FEVD at horizon 10 (**Table 6**) measures the relative contribution of shocks to the fluctuations of each variable. The outcomes show that own innovations account for most of the variance in each series, which indicates a high degree of partial independence among the three systems. The digital economy accounts for around 2.3% of the variation in agricultural innovation at horizon 10, indicating that the two phenomena are increasingly linked, albeit still to a limited extent.

Overall, the FEVD results are consistent with the impulse response analysis: linkages exist but remain relatively contained, which helps explain why stage-dependent heterogeneity emerges so prominently in the subsample estimations.

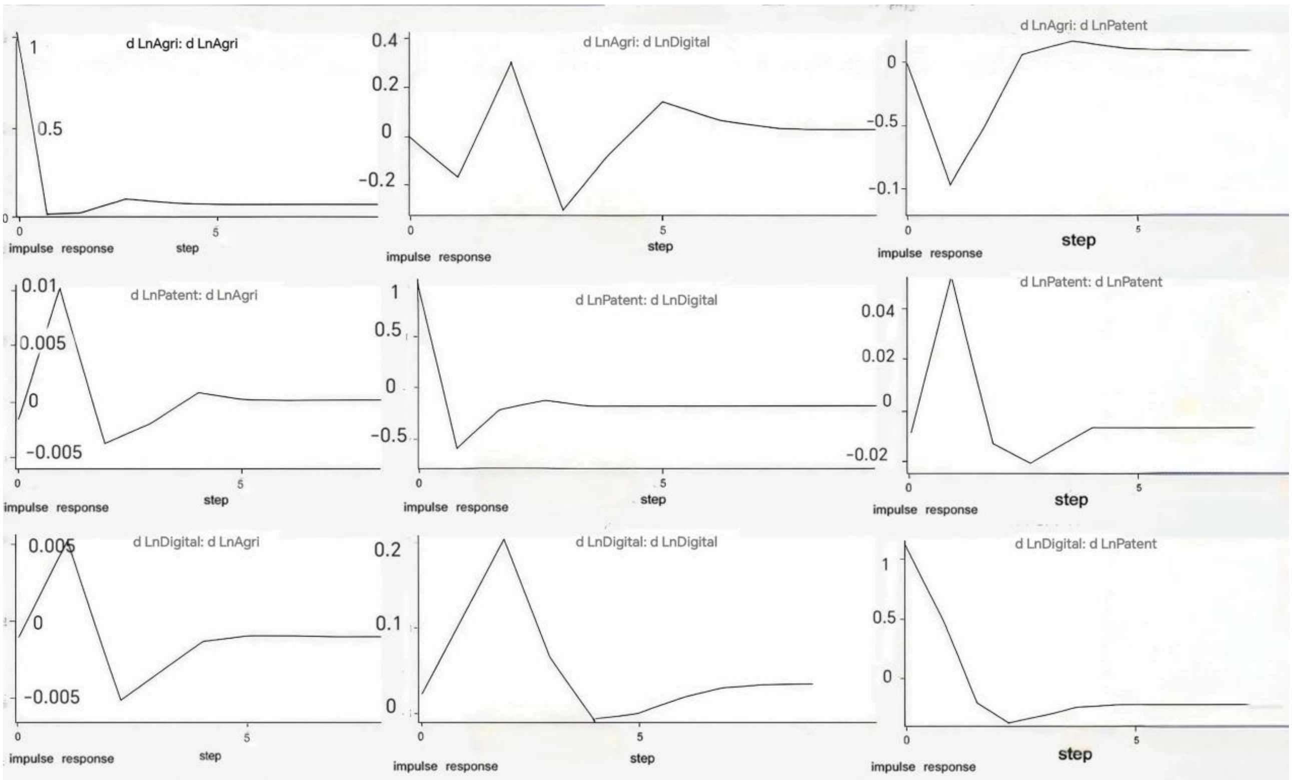

Figure 2. Impulse Response Functions.

Source: Author's calculations based on Stata 18.

Table 6. Variance Decomposition at Horizon 10 (%).

Shock Source	lnAgriculture	lnpatent	lnDigital
d.lnAgriculture	98.9	0.9	0.2
d.lnPatent	0.7	97	2.3
d.InDigital	2.3	0.6	97.1

Source: Author's calculations based on Stata 18.

4. Heterogeneity Analysis and Robustness Checks

4.1. Heterogeneity Analysis

To examine stage-dependent dynamics more explicitly, the PVAR model is re-estimated separately for developed, emerging, and developing economies. The results from the subsample provide strong support for H3, with key coefficients summarized in **Table 7**.

- In developed economies, there exists a notable bidirectional relationship between the digital economy and agricultural innovation. This phenomenon signifies the existence of a synergistic phase in which knowledge creation and knowledge application reinforce each other.
- Agricultural growth in emerging economies has a strong negative impact on digitalization in the short run, signifying a growth-led digitalization pathway with large and negative structural adjustment

costs [10, 11].

- In developing market economies, none of the three systems show statistically significant interactions, which indicates that agriculture, innovation, and digitalization are largely decoupled, and knowledge-based drivers [5, 6] are not yet in place.

Table 7. Key Coefficients from Heterogeneity Analysis (Subsample PVAR Estimates).

Dependent Variable	Independent Variable	Developed Economies	Emerging Economies	Developing Countries
d.LnDigita	L1.d.LnAgricultural	0.215 (0.108)	**−0.802** (0.013)	−0.051 (0.891)
d.LnDigita	L1.d.LnPatent	**0.254** (0.043)	0.069 (0.384	0.040 (0.872)
d.LnPaten	L1.d.LnDigital	**0.288** (0.038)	0.106 (0.577)	−0.071 (0.654)

Note: *p*-values in parentheses; bold indicates significance at the 5% level.
Source: Author's calculations using Stata 18.

The group differences analysis supports the stage-dependent model. In advanced economies, the significant two-way links between digitalization and innovation indicate that these economies now have a mature knowledge-based agricultural system with digitalization occurring not just at the farm level but also at the research and development level. In emerging economies, agricultural growth impacts digitalization adversely in the short run due to turbulence, as the quick growth of sectors strains capabilities and investment is diverted away from digitalization. In less developed nations, the statistical uncoupling of the three systems uncovers a deeper "digital divide" wherein agriculture and agribusiness sectors operate largely in isolation from new digital and innovation systems.

The findings suggest that policy tools cannot employ universal off-the-shelf digital solutions. In developing countries, the main constraints blocking progress are primary capabilities, namely education, institutional capability, and digital literacy, and not access to individual technologies. In emerging economies, it is important that policy fosters adjustment cost alleviation and complementary investment, so that speedy growth does not pre-empt digital upgrading. In developed economies, strengthening open innovation networks and data-sharing platforms can further enhance the observed bidirectional linkages.

The range of cross-stage differences indicates the importance of institutional and cultural backgrounds. Feedback loops between digitalization and innovation in advanced economies are quickened through strong intellectual property regimes, active venture-capital markets and institutionalized public–private partnerships in agricultural R&D. Emerging economies face weak enforcement of intellectual property rights, fragmented innovation policies, and underfunded extension services that limit the translation of digital adoption into sustained innovation efforts. Developing countries are technologically slow due to their underdeveloped credit markets, rural-urban divide and lack of human resources. It is crucial to recognize these "soft infrastructure" limitations for designing realistic digitalization strategies.

4.2. Supplementary Mechanism Evidence

To further probe the mechanisms underlying stage-dependent dynamics, a within-stage fixed-effects panel regression is estimated, relating the Digital Economy Index to the logarithms of agricultural value added and agricultural patents:

$$Digital_{\mathrm{it}} = \alpha_i + \beta_1 \ln(Agricultural_{\mathrm{it}}) + \beta_2 \ln(Patent_{it}) + u_{\mathrm{it}}$$

The results reveal distinct patterns across stages. In developed economies, β2 (innovation) is strongly positive and statistically significant ($\approx$39.7, t $\approx$ 3.8), while β1 (agricultural output) is small and insignificant, indicating that digitalization is primarily associated with innovation rather than mere scale effects. In emerging economies, β1 is large and highly significant ($\approx$91.9, t $\approx$ 11.9), whereas β2 is effectively zero, suggesting a growth-driven digitalization mechanism. In developing economies, both coefficients are positive and significant (β1 $\approx$ 39.6, β2 $\approx$ 9.9), implying that digitalization is linked to both scale and incremental innovation, but at much lower absolute levels.

These supplementary results complement the

PVAR-based evidence and are fully consistent with the stage-dependent framework: in advanced economies, digital tools are tightly integrated with innovation processes; in emerging economies, digitalization follows agricultural expansion; and in developing economies, both channels operate but from a structurally low base.

4.3. Robustness Checks

Several robustness checks were conducted to assess the stability of the main findings. First, the Digital Economy Index was replaced by alternative proxies—ICT service exports and high-technology exports—and the core results remained qualitatively unchanged. Second, all continuous variables were Winsorised at the 1st and 99th percentiles to mitigate the impact of outliers; this did not alter the sign or significance of the key coefficients. Third, the model was re-estimated for a restricted period (2010–2021), and similar patterns of causality and heterogeneity were obtained. Taken together, these checks confirm that the stage-dependent dynamics identified in the benchmark specification are robust to alternative measures, outlier treatment, and sample periods.

5. Conclusion and Policy Implications

5.1. Conclusions

This study provides systematic empirical evidence of stage-dependent interactions among the digital economy, agricultural technological innovation, and agricultural growth in Asia-Pacific economies. Using both full-sample and subgroup analyses, agricultural growth is shown to be a key short-run driver of digital uptake, while the nature and strength of digital–innovation linkages vary with the level of development. In particular, developing economies exhibit weak and statistically insignificant linkages, emerging economies follow a growth-led digitalization pattern, and advanced economies display mutually reinforcing, two-way relationships between digitalization and innovation.

These findings contribute to the literature on the knowledge economy by demonstrating that the co-evolution of digitalization and innovation is conditioned by the development stage. The study refines existing theory and offers empirical validation of a stage-dependent framework for agricultural transformation in the digital era.

It also asks when, how, and under what conditions the digital economy matters for agriculture, whereas the other question is "Does the digital economy matter?" We must classify the position of the economy on the scale of development if appropriate policy prescriptions are to be devised. For example, deploying AI-enabled precision agriculture in places with poor digital infrastructure and low capacity for innovation will have disastrous results with large resource misallocation. Advanced economies will not be able to maximize existing synergy cycles with a single-mindedness towards basic connectivity. Usually, it is important for national digital agriculture strategies to consider the specifics of context, sequencing, and diagnostics.

5.2. Policy Implications

The empirical findings do not support one-size-fits-all strategies for digitalization. A clear diagnosis of structural conditions in each economy should be explicit in policy stage specificity.

5.2.1. Developed Economies: Deepen Synergistic Integration

Developed economies exhibit a balanced framework in which the digital economy and agricultural innovation mutually reinforce each other. The priority of policy should be to strengthen this synergy rather than only expand basic infrastructure. Relevant measures include:

- fostering public–private partnerships for frontier agri-tech R&D (e.g., AI-based farm management, genomics, robotics);
- establishing robust data-governance frameworks that enable secure data sharing while protecting privacy;
- investing in advanced skills (data science, IoT engineering, remote sensing) tailored to the agri-food sector [7, 8, 30].

The overarching objective is to consolidate and extend the virtuous cycle already observed between digitalization and innovation.

5.2.2. Emerging Economies: Manage Transition and Adjustment Costs

In many of the world's emerging economies, digitalization happens primarily under growth stimulus. Despite all this, the growth continuum comes with short-term adjustment costs. Thus, the policy should mediate between expansion and transition management. To mitigate the resource reallocation pressure indicated by the empirical results from the research, when producers invest at once in both conventional and digital assets, the enforcement of complementary credit and risk-sharing mechanisms is imperative. We also need a stronger digital agriculture extension system with institutional reforms to secure land and data rights, and clarify data-use regulations. At the same time, opening up collaborative marketing platforms, such as local agri-e-commerce, social media-based branding, and community-supported agriculture (CSA) schemes, can help farmers convert digital adoption directly into higher incomes by connecting them with larger local and global markets.

5.2.3. Developing Economies: Build Foundational Capabilities

The disconnect between the agriculture sector, innovation, and digitalization in developing economies suggests that it would be too early to focus on advanced digital technologies. Our first priority is to build the base capabilities needed for future digital agriculture. This includes:

- investment in basic infrastructure (rural roads, reliable electricity, mobile connectivity);
- strengthening general and vocational education, particularly in basic agronomy and digital literacy;
- reinforcing public agricultural research and extension institutions as key intermediaries [6, 31].

Concurrently, initial steps toward digital collaboration can be encouraged. Policy could support pilot programs for digitally-enabled cooperative models, such as linking farmer groups to institutional buyers via simple mobile platforms or establishing basic community-supported agriculture (CSA) schemes with online payment functionalities. These initial forays help build digital literacy and market awareness at the grassroots level, creating a foundation for more advanced marketing strategies in the future.

The aim is to create the minimum institutional and infrastructural platform upon which future digital and innovation systems can effectively operate.

The empirical evidence from developing nations indicates a digitalization pathway driven by growth, but a huge short-term adjustment cost. A quick expansion in agriculture may temporarily crowd out digital investment. Policies must proactively guide the process of change, rather than allow pressures to hamper modernization. One of the main strategies is to reduce these costs by ensuring that digitalisation results in higher and more stable incomes for farmers, so that the costs are justifiable. The advanced digital collaborative marketing models will help farmers appropriate larger shares of market growth [12]. Specifically, support should be directed towards:

- Establishment of localized agricultural e-commerce platforms: Organizing dispersed producers together, setting up common supply chain standards, and establishing direct connections with consumers or bulk buyers allows farmers to achieve economies of scale which individual farmers cannot and helps to offset adoption costs.
- The promotion of social media and content marketing: training farmers to use social media (e.g. WeChat, Facebook, TikTok) for branding and storytelling builds consumers' emotional connection and trust with their products, which increases the consumer's perception of value and creates a premium that assists in recouping the digital investments.
- The Institutionalization of digitally enhanced models such as Community Supported Agriculture (CSA): Digital platforms that scale up CSA and subscription agriculture make ordering, managing and payment easy. This reduces the adjustment costs of production and market uncertainty, which are among the most significant costs that farmers face.

Beyond national policies, stage-specific strategies should be embedded in regional cooperation frameworks. Developed economies can provide knowledge-sharing platforms and technical assistance; emerging economies can adapt and intermediate these solutions to local conditions; and developing economies can benefit from joint initiatives in digital literacy, pilot projects, and infrastructure development supported by multilateral organizations. Such differentiated cooperation, explicitly recognizing heterogeneous stages, can accelerate the reduction of the agricultural digital divide and strengthen regional resilience.

5.3. Research Limitations and Future Directions

This study faces several limitations. The sample is restricted to 15 Asia-Pacific economies, which may limit generalisability. Future work could extend the analysis to other regions to test the external validity of the stage-dependent framework.

Although the present measures of digitalization and innovation are constructed to be as comprehensive as possible, data constraints remain. The adoption choice and its impacts could also be studied at the micro-level by integrating micro-level survey data, such as agribusiness modules from the World Bank Enterprise Surveys or household-level datasets like China Family Panel Studies (CFPS). We could also take a similar approach to developing more sophisticated structural indicators which capture aspects of digital migration. For instance, we could develop a Digital Agricultural Transformation Index which captures the penetration of smart agricultural machinery, subscriptions to agricultural software as a service (SaaS) solutions and adoption rates of remote-sensing-based precision farming. The improvements would greatly enhance the depth and precision of any future analysis.

Several methodological extensions are also promising. The universality and boundary conditions of the stage-dependent framework could be clarified by applying this to a global sample. Another potential application of dynamic models is their ability to shed light on the "black box" of how digitalization influences agricultural growth through innovations, and whether different types of innovations (e.g., product vs process) respond differently to digital shocks. Another important use of spatial econometric approaches includes identifying cross-border spillovers, such as technology spillovers, taking place from the developed to the emerging economies in regional value chains. Ultimately, case studies of qualitative nature that cover economies in transition across stages could be helpful in elucidating the political, institutional and social factors that enable or constrain the transitions. The macro-econometric results can be enriched through that context [32].

It is recommended that future research engage the environmental and climate facets of the digital–innovation–agriculture nexus. The current framework focuses more on economic and technological linkages. But many Asia-Pacific economies are very vulnerable to climate change, resource scarcity, and degradation of ecosystems. By adding indicators like carbon efficiency, water-use optimization, and biodiversity outcomes, a bigger picture would emerge about how digital technologies and innovation contribute to not just productivity but also resilience and sustainability. In the region, linking digital transformation to growth and climate-resilient development will be crucial to the formulation of sustainable agriculture.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Acknowledgments

The author would like to thank the editor and anonymous reviewers for their constructive comments.

Conflicts of Interest

The author declares no conflict of interest.

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