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Agricultural digitisation and agricultural development: A comparison between developed and developing countries

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Abstract

Agricultural digitisation is one of the key drivers of agricultural development, as well as of rapid economic growth, in many countries. This study aims to investigate the causal links between agricultural digitisation and high-quality agricultural development in the context of developed and developing countries. To this end, we apply a cross-sectional autoregressive distributed lag (CS-ARDL) approach and method of moments quantile regression (MMQR) to explore the association between these variables in four quantiles ($Q^{0.25}$, $Q^{0.50}$, $Q^{0.75}$, $Q^{0.90}$) to analyse panel data from the period 2010 to 2024.The empirical results of the CS-ARDL-MMQR technique show that agricultural digitisation has a significant and positive impact on the development of high-quality agriculture at a 1% statistical level in both panels in the long run. The impact of agricultural digitisation and agriculture value added is more evident in developed countries. In the context of developing countries, agricultural digitisation is found to be too insignificant to have an effect on the development of high-quality agriculture. Besides, a heterogeneity analysis showed that agricultural digitisation played a more significant role in developed countries than in developing countries. The results of the Dumitrescu-Herlin (DH) causality test show that the majority of the variables had one-way causality towards the development of high-quality agriculture in both panels, except for the agricultural digitisation and development of high-quality agriculture, which had two-way causality in developed countries only. The empirical findings suggest that, through improved agricultural digitisation in developed countries, more funds could be invested in agricultural digitisation projects to adopt the development of high-quality agriculture in developing countries.

Key words: agriculture, digitisation, development, CS-ARDL approach, MMQR technique, developed and developing countries

1. Introduction

The agricultural sector faces significant challenges, including resource constraints, ecological degradation, and market volatility, necessitating systemic transformation. This requires reimagining practices for resilience, inclusivity and ecological integrity, amidst complex rural-urban interfaces. On the other hand, agricultural modernisation requires the integration of the digital economy with traditional agriculture, aiming for increased productivity, economic efficiency, social welfare and environmental sustainability. Rapid advances in science and technology, such as digitisation, automation and artificial intelligence, have significantly improved informatisation, intelligence, and precision in agricultural production, making systems more sustainable and efficient.

In this regard, this paper understands digital agriculture (DA) to deal with the practice of advanced technological solutions, such as sensors, robotics and data analysis, to improve the ecological and economic viability of agricultural operations, and simultaneously elevate crop output and quality. Conventional farming methods have faced significant challenges in the past three decades in responding to the increasing demand for food, rising labour costs, reducing their carbon footprint, and climate change. At the same time, high-quality agricultural development (QAD) is required that involves utilising agricultural science and technology innovation, promoting multi-industry integration, greening production methods, extending industry chains, enhancing product value, improving efficiency, increasing farmer incomes, ensuring product supply, and bridging urban-rural development gaps

According to Izmailov (2019), Zhao and Xu (2021), Xie *et al*. (2022) and Zhang *et al*. (2022), agricultural digitisation digitises and manages the agricultural production process, production environment and agricultural product sales and circulation, leading to a reduction in production costs and sales costs of agricultural products. The effect of this in developing countries may be either positive or negative, according to the theoretical analysis done. There is a strong disparity between modern and more traditional agriculture. In the former, remote sensing, geographic information systems, global positioning systems, computer technology, communication and network technology, automation technology and other high and new technologies are taken as agricultural production factors. With modern information technology applied to visualise levels of agriculture across developed and developing countries, this creates a research gap for empirical analysis and comparison of these two groups of countries to examine the real effects in the respective countries. In short, the existing literature on the nexus between agricultural digitisation and the development of high-quality agriculture gives rise to the following research questions:

- Does agricultural digitisation display similar behaviour in both developed and developing countries, irrespective of having different levels of economic development?
- Does the variation in agricultural digitisation in the two groups affect this relationship?
- Do the trends in mostly economic variables result in cross-sectional correlation and co-integration in either or both groups?

This study was designed to evaluate the behaviour of agricultural digitisation in relation to the development of quality agriculture using multinational datasets (panel study) of different countries and regions, and might be helpful to answer these questions and fill the gap in the existing literature.

Thus, the contribution of the study at hand could including the following ways. Firstly, this study develops an agricultural digitisation index comprised of sub-components: average computer ownership per 100 rural households; average number of mobile phones owned by each 100 rural households; rural users with broadband access; length of rural delivery route; financial basis for digital agriculture; digital inclusive financial payment index; digital inclusive financial insurance index; digital inclusive financial credit index; use of computer tablets for agricultural purposes; use of drones for security and other monitoring purposes; use of drones for precision agriculture (supply of visual/phenological data); use of robots for agricultural purposes (irrigation, fertilisation, planting, etc.). This is in contrast to the existing literature, which uses ownership of a smartphone, a traditional phone, a computer or a tablet with access to a current internet subscription (Gülter *et al*. 2018). The ability to move files across digital devices (such as a computer and smartphone), a cell phone, a camera, etc. improves the capability of using and connecting gadgets to a computer (Sulak 2019). The adequacy of access to a home web service, the adequacy of access to a mobile web service, satisfaction with home web speed, satisfaction with mobile web speed and the use of programs that give consultancy services via mobile telephones are all important (Awol 2020). There are a significant number of studies highlighting the contribution of digitalisation of agriculture to climate change issues. However, works using the digitalisation of agriculture as a proxy for the development of quality agriculture are limited.

Secondly, as industrialised nations contribute to agricultural digitisation, farming techniques are being transformed by incorporating digital technologies to improve productivity, sustainability, and efficiency. This entails optimising resource allocation, monitoring crops, and automating tasks using instruments like sensors, drones, artificial intelligence and data analytics. For instance, 27.6% of agricultural production was digitalised by 2023. Field crop planting has also become digitalised, at a pace of 26.4%, and 10.5% of China's value-added agricultural output is currently derived from the digital economy (Zhang & Zhu, 2025).

Thirdly there are studies that take into account agricultural digitisation, the level of high-quality agricultural development and the components of the agricultural digitisation index. It is significant to understand the relationship among these variables to gain insight into how agricultural digitisation affects agricultural development and food security. Therefore, wavelet analysis was used to discover the relationships among these variables. This study focuses on identifying the co-movement between agricultural digitisation, the level of high-quality agricultural development. Developing nations, on the other hand , must face the expense and are unable to invest in agricultural digitalisation because of the scarcity of resources. Also, because they lack connectivity and infrastructure, have restricted access to digital skills and technology, lack suitable finance, face worries about data security and privacy, and have to endure a lacklustre regulatory environment in some nations, farmers are often reluctant to adapt and adopt technology. This demands a comparative study to evaluate how agricultural digitisation works in developed countries and what kind of negative effects arise in developing countries, since there is no previous such comparative study in the literature (Abbas *et al*. 2022; Elahi *et al*. 2024).

Finally, methodological additions have been made to the empirical literature. Sigmund and Ferstl's (2021) innovative 'cross-sectionally augmented autoregressive distributed lag', or CS-ARDL, is an economic technique used to analyse panel data, particularly when the cross-sectional units (such as countries or regions) exhibit cross-sectional dependencies. They combine the benefits of ARDL (autoregressive distributed lag) models with the ability to handle cross-sectional dependence, endogeneity, and serial correlation. In addition, the moments method can be used when working with complex data structures or concentrating on particular regions of the conditional distribution of the outcome variable, such as quantile regression. This (MMQR) is a statistical technique that combines the concepts of quantile regression and the method of moments to estimate model parameters. Compared to conventional approaches that only consider the mean, it enables the estimation of parameters across several quantiles of the dependent variable, offering a more thorough knowledge of the relationship between variables. This is the first study on agricultural digitisation and the development of quality agriculture using the new approach, and there are not many studies using this particular methodology. To answer the above research questions, the following are the specific objectives of the study:

- To investigate the causal relationship between agricultural digitisation and quality development of agriculture in selected developing countries and developed countries.
- To make a comparison of the behaviour of agricultural digitisation and quality development of agriculture in developing countries and developed countries.
- To provide policy recommendations for the development of quality agriculture in the two groups on the basis of the empirical findings of the study.

This study utilises cross-sectional autoregressive distributed lag (CS-ARDL), which is an advanced framework to address cross-sectional dependence and endogeneity in empirical models. We also use the method of moments quantile regression to explore the association between these variables in four quantiles ($Q^{0.25}$, $Q^{0.50}$, $Q^{0.75}$, $Q^{0.90}$) to analyse panel data from the period 2010 to 2024 to investigate the causal relationship between agricultural digitisation and the development of quality agriculture in selected developing countries and developed countries.

2. Conceptual framework of the development of high-quality agriculture

High-quality agricultural development is crucial for food security, sustainability and environmental stewardship, as the global population is projected to reach 9.7 billion by 2050. Scientific and technological innovation plays a significant role in enhancing agricultural productivity and resilience. Understanding the spatial mechanisms of scientific and technological innovation can help policy makers identify areas of high potential for high-quality agricultural development and target interventions effectively. This study aims to explore the spatial boundaries and mechanisms of the effect of scientific and technological innovation on the development of high-quality agriculture to shed light on how to promote sustainable agricultural development. There is debate on whether to use a comprehensive evaluation method or a single-indicator method, with the single-indicator method allowing easier comparison between results (Qin & Chen 2024).

High-quality agricultural development goes beyond increasing production volumes and improving financial returns. It involves refining practices, enhancing industry efficiency, and optimising production systems. This process integrates scientific advancements and reforms traditional institutions, aiming to optimise agricultural productivity. The goal is to achieve improvements on multiple fronts, including economic, social and environmental outcomes. It focuses on enhancing total factor productivity, increasing farmers' income, and modernising agriculture through advanced technologies and management practices. In addition, agricultural digitisation is driving high-quality agricultural development by facilitating investment, breaking down barriers to technological R&D, and fostering an innovation ecosystem. This has led to the development of technologies like precision agriculture, mechanised farming and eco-friendly practices. These innovations reduce waste, improve product quality and increase economic returns for farmers (Zhongsheng, 2025). They also promote sustainable practices, strengthen agricultural resilience against external shocks, and transform the entire agricultural value chain. The integration of digital technologies, advanced supply chain management and big data analytics enables the transition from traditional farming methods to modern, data-driven practices. In order to assist farmers in making both short-term and long-term decisions, modern farms are utilising a variety of ground-based sensors, maps, drone-generated photos, artificial intelligence and prediction models to provide comprehensive agronomic data on crop conditions. Future farms are anticipated to be fully networked because of advancements in wireless communication and high-performance data-processing gear. In this sense, digital agriculture offers a great opportunity for creative approaches to automation and robotics, which will free up human labour for fieldwork and give farmers more time to concentrate on creating agribusiness and scientific farming practices, as shown in Figure 1.

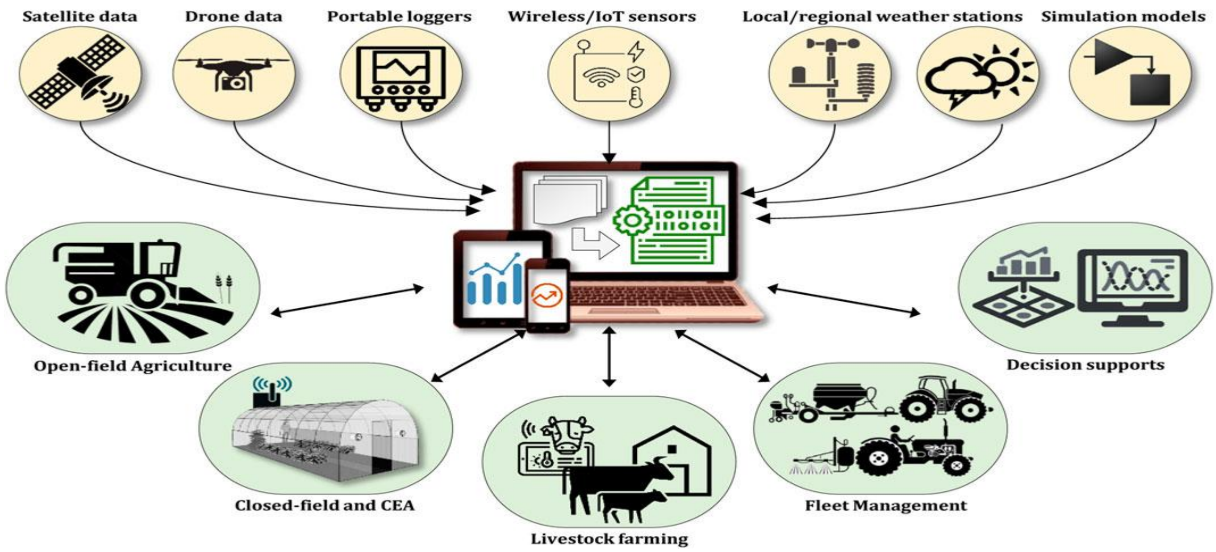

Figure 1: Agricultural digitisation and agricultural development level
Source: Shamshiri *et al.* (2024)

Digital agriculture uses advanced technology to improve accuracy and efficiency in crop production. AI, big data and cloud computing can optimise resource allocation, reduce waste and enhance product quality. They also facilitate intelligent crop storage and processing analyses, providing producers with scientific cultivation suggestions and sales strategies. Real-time monitoring of crop growth and development reduces agrochemical use and soil and water pollution. Digital technology facilities can foster a circular economy by utilising livestock manure, crop residues and agricultural waste for resource conversion. Promoting high-quality agriculture is crucial. At a compound annual growth rate (CAGR) of 12.80% from 2022 to 2030, the global digital agriculture market is projected to reach USD 34.13 billion. The market for digital agriculture is anticipated to expand dramatically over the forecast period as a result of technological advancements, resource efficiency and waste reduction, yield maximisation, and strategic government policies that increase public awareness and support the adoption of digital agriculture (see Figure 2).

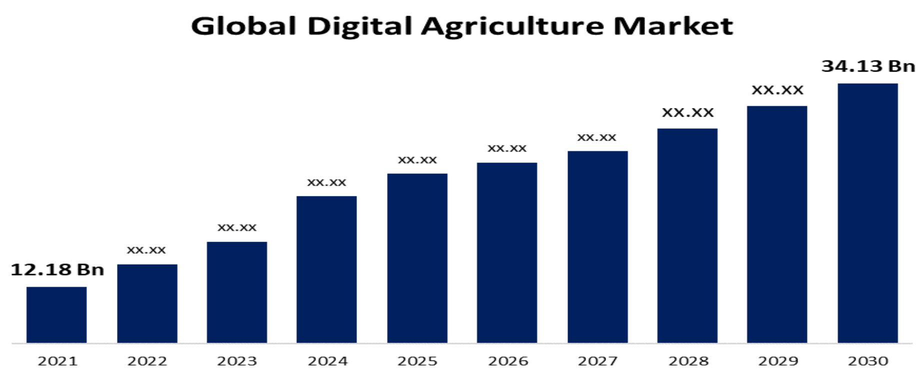

Figure 2: Agricultural digitisation and agricultural development level
Source: Straits Research (2025)

There are also reports on the size, share, and trends of the digital agriculture marketplace by product type (perishables, non-perishables, agri-rural materials), by offering (hardware, software, services), by technology (variable rate application, remote sensing technology and guidance technology), forecasts for 2025 to 2033 by application (variable rate application, field mapping, yield monitoring, crop scouting, weather tracking and forecasting, inventory management, farm labour management, financial management) and others (demand forecasting, customer management, payables and receivables), as well as by region (North America, Europe, Asia-Pacific, the Middle East and Africa, and Latin America (see Figure 3).

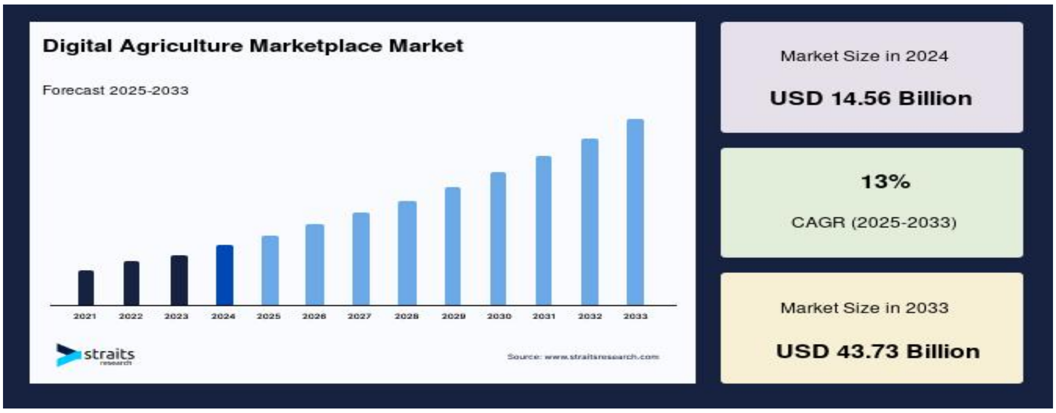

Figure 3: Agricultural digitisation and agricultural development level
Source: Straits Research (2025)

The size of the global digital agriculture marketplace market was estimated at USD 14.56 billion in 2024 and is expected to increase at a compound annual growth rate (CAGR) of 13% from 2025 to 2033 – thus from USD 16.45 billion in 2025 to USD 43.73 billion.

The potential for sector digitalisation is innovative, even though the use of data in agriculture is not a novel idea. The technologies utilised to gather, store, process, manage and disseminate information at the farm level, as well as the quality of that information, are additional factors. Real-time monitoring of some parameters has been made possible by advancements in sensor technology, while improved process automation has been made possible by robotics (Araújo *et al*. 2021). Furthermore, cheaper and easier access to computing power has aided in the development of new decision support systems for improved agricultural management. Big data, for example, facilitates a large amount of historical and real-time data, which AI-based techniques convert into knowledge that can be put to use. The data flow between the technologies is depicted in Figure 4. According to the FAO *et al*. (2021), agricultural digitisation boosts productivity, efficiency and resource management, all of which have a favourable effect on agricultural growth. It minimises production risks, optimises inputs like fertiliser and insecticides, and helps farmers make better decisions by giving them access to real-time data. In addition, digital technologies increase supply chain transparency, open up new markets, and have the potential to improve government services.

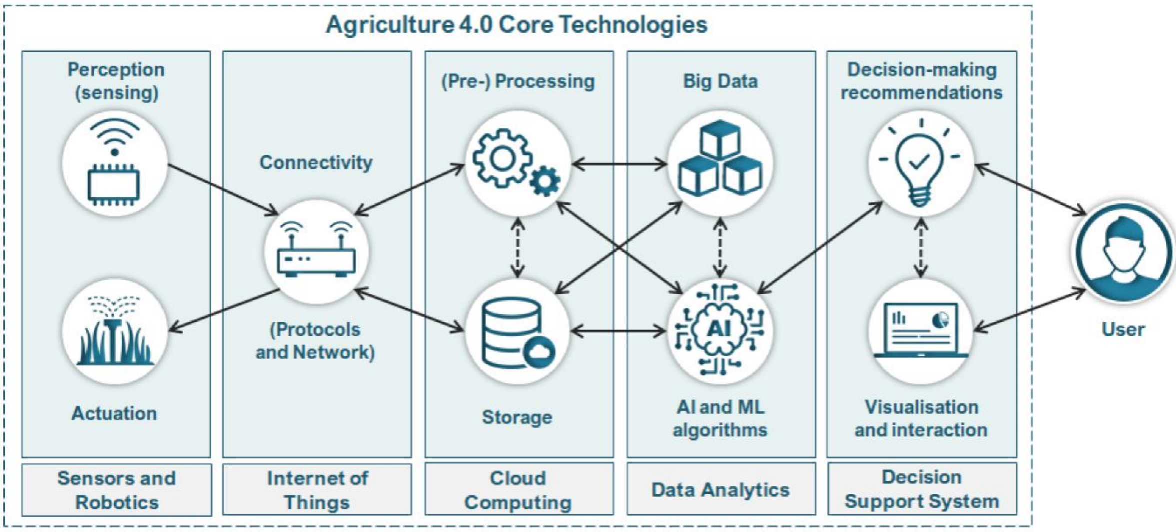

Figure 4: Agricultural digitisation
Source: Araújo *et al*. (2021)

The agricultural digitisation paradigm consists of five main stages: sensor and robotics, internet of things (IoT), cloud computing, data analytics, and decision support systems, each enhancing data flow and system functionality. As a result, the digitisation of agriculture raises the level of agricultural growth by giving farmers a wide range of instruments to tackle issues related to food production (shown in Figure 5), including crop losses, sustainability, environmental effects and farm productivity. For example, farmers can monitor and manage farm activities remotely, regardless of time or location, using IoT-enabled devices comprising wireless sensor networks. On farmlands, hyperspectral camera-equipped drones can gather data from a variety of sources, and autonomous robots can help with or complete repetitive chores. Computer programs can be utilised to help farmers make decisions by analysing the collected data using data analytics techniques. The same is true for smart agriculture, which uses modern systems to monitor and analyse a wide range of parameters related to environmental factors, weed control, crop production status, water management, soil conditions, irrigation scheduling, herbicides and pesticides, and controlled environmental agriculture. The goal is to increase crop yields, minimise costs, improve product quality and maintain process inputs (Ozdogan *et al*. 2017).

Figure 5: Digital agriculture practices in the context of agriculture 4.0
Source: Ozdogan *et al.* (2017)

3. Literature review

There is a battery of literature that focuses on the potential impact of agricultural digitisation on the development of quality agriculture, such as on agriculture 4.0 (Rose & Chilvers 2018; Da Silveira *et al*. 2021) and machine learning tools for data processing (Sharma *et al*. 2020, 2021). Digitalisation in agriculture utilises data-rich software, hardware and services to enhance productivity and efficiency and to reduce costs and work effort, while improving environmental protection and agricultural externalities (Charatsari *et al*. 2020; Fielke *et al*. 2020) and promoting smart agriculture (Grogan 2012; Wolfert *et al*. 2017). Digitalisation in agriculture has led to the emergence of new technology forms and data-driven agriculture, which is often referred to as digital agriculture. (Liang *et al*. 2003), open-source robotics software (Mier *et al*. 2023), and low-power wide-area networks for internet of things applications (Klaina *et al*. 2020). These technologies have redefined the preexisting ideas of precision agriculture and smart farming. Overall, these studies show that farmers' business practices are changing rapidly as a result of the digitalisation of agriculture. Farmers can now operate with greater precision, productivity and efficiency thanks to the use of cutting-edge technologies. Digitalisation makes it possible to monitor and manage crops in real time, which increases yields and decreases waste. The application of digital technologies in agriculture is influencing the delivery of ecosystem services, which are influenced by the food systems in which they are embedded. International actors, like the World Bank, FAO and OECD, envision future food systems prioritising technology for maximising food output. This vision aligns with the long-standing narrative that technology enhances food security (Lajoie-O'Malley *et al*. 2020).

Tang and Menghan (2022) examined the impact of agricultural digitisation on high-quality agricultural development. They considered three perspectives: enhancing production efficiency, optimising resource allocation, and upgrading the industrial structure. The research uses China's provincial panel data from 2011 to 2020 to verify the hypothesis. The results show that agricultural digitisation promotes high-quality development, with a single threshold effect based on the education level of the rural labour force. Three policy suggestions are made: improving agricultural digitisation infrastructure, considering regional development differences, and improving the quality of the rural labour force and input from scientific and technological talent. Fu and Zhang (2022) explored the impact of regional digitalisation levels on agricultural total factor productivity using China's provincial panel data from 2013 to 2020. The results show that digitalisation can significantly increase productivity in economically underdeveloped areas, but not in economically developed ones. Mitigating factor market distortion and large-scale production can strengthen this effect.

Bocean (2024) explored the impact of digital technologies on agricultural productivity in EU countries. The study uses equation modelling, artificial neural networks and cluster analysis to analyse the relationship between digital technology use and productivity. The results show significant associations between digital technology use and labour force productivity, emphasising the importance of embracing digital technology for enhancing agricultural productivity. Future research could focus on strategies to promote widespread adoption and longitudinal analyses for policy interventions to examine how digitisation is affecting agriculture, with a particular emphasis on the automation of open-field and closed-field cultivations (Shamshiri *et al*. 2024). Shamshiri *et al*. (2024) talk about the advantages of digitisation, like improved productivity, sustainability, and lower input consumption. The study does, however, also point out difficulties with scalability, dependability and high costs. Existing configurations are costly and custom-designed, which makes them unsuitable for broad use. The assessment highlights the need for more development and implementation of digital solutions and provides insights for industry players, policy makers and scholars in the field.

Quan *et al*. (2024) examined the impact of digital technology on agricultural economic resilience in 30 Chinese provinces from 2011 to 2020. They find a continuous strengthening of digital technology development in China, with significant polarisation and spatial imbalances. The resilience of the agricultural economy fluctuates, with a notable upward trend. Digital technology plays a pivotal role in empowering resilience through agriculture-scale operations, industrial transformation and technological progress. Guo *et al*. (2025) developed a comprehensive index system to evaluate agricultural digitisation and its economic resilience in 30 Chinese provinces from 2012 to 2022. Their study found that digitisation can improve agricultural resilience, with higher effects in major grain-producing areas and in the eastern regions. The consumption structure upgrading of rural residents also strengthened the promotion effect of digitalisation. Digital technology-inclusive finance also affected agricultural digitisation. To improve agricultural resilience, decision makers should consider the enabling effect, regional heterogeneity and the development of digital technology-inclusive finance.

4. Empirical framework

4.1 Data

We used a panel dataset for seven selected developed countries (N = 7), namely Canada, France, Germany, Italy, Japan, the United Kingdom and the United States, over the period from 2010 to 2024 (T = 14), so the number of observations was 98. We also used a panel dataset for seven selected developing countries (N = 7), namely India, Brazil, Argentina, Algeria, Egypt, Tunisia and Malaysia, over the period from 2010 to 2024 (T = 14), so the number of observations also was 98. The was done to identify the long-term and short-term impact of agricultural digitisation on the development of high-quality agriculture and to understand the dynamic effect of agricultural digitisation on high-quality development of agriculture. The following table describes these variables.

Table 1: Definition of variables

Variables and types of variables		Abbreviation	Units	Data source
Dependent variables	High-quality agricultural development[1]	QAD	By taking into account aspects like sustainability, efficiency and social impact, in addition to production volume, a high-quality agricultural development (HQAD) index evaluates the general development and calibre of agricultural systems. It serves as a means of assessing how successfully agricultural methods support more general development objectives, such as environmental preservation and rural rehabilitation.	World Bank

[1]Agricultural quality development (Quality). Total factor productivity has been employed by academics to assess the calibre of agricultural progress. However, because it only has one indication, total factor productivity is insufficient to fully summarise and generalise, and is not comparable with the indicators of quality development. With a greater focus on multidimensional coordination, as well as economic, ecological, environmental and social aspects, we summarise earlier research in this paper that ‘high quality’ refers to an innovation that attempts to meet people’s desires for a better and upgraded life in accordance with current economic development. This study develops a comprehensive index system for high-quality agricultural growth, including agricultural endowment, agricultural production level, agricultural greenness, and sustainable social development. It uses the entropy value approach to calculate China's agricultural quality index through entropy value and weighting. The study uses four basic indicators and 17 supplementary indicators to estimate the quality of agricultural growth. In conclusion, there is not a single ‘high-quality agricultural development by country index’, but rather a variety of metrics and strategies that emphasise social justice, efficiency and sustainability to be employed to evaluate and encourage this kind of development.

Independent variables	Agricultural digitalisation[2]	AD	Digital agriculture, or digital farming, refers to the application of digital technologies in agriculture to improve the efficiency, sustainability and profitability of agricultural production. This involves the use of sensors, smart grids, data analytics tools, automation and robotics to optimise agricultural processes throughout the value chain.	World Bank
Control variables	Agriculture value added	AG	Following the adjustment for intermediate inputs, the agriculture value-added index calculates the net output of the agricultural sector, which includes forestry, hunting and fishing. The contribution of the sector to the national economy is reflected in this figure, which is frequently given as a percentage of GDP. This measure is essential for comprehending agricultural output and how it contributes to economic expansion.	World Bank
	Gross domestic product	GDP	GDP is the total monetary value of all finished goods and services produced inside a nation's boundaries over a given time period, usually a quarter or a year. Indicators of a country's overall health and economic activity are crucial. There are other methods for calculating GDP, such as the income method (which adds up all of the money made from production) and the expenditure method (which adds up all of the money spent on goods and services).	World Bank
	Trade openness	TO	A country's level of international trade participation in relation to its total economic size is shown by the trade openness index. The ratio of a nation's total commerce (imports plus exports) to its GDP is how it is typically computed.	World Bank
	Employment in agriculture	EA	The percentage of workers in the agriculture industry relative to all workers is represented by the employment in agriculture index. According to the World Bank, 26.37% of the world's workforce was employed in agriculture in 2022. However, this percentage differs greatly by location, with Europe claiming the lowest share, at 5%, and Africa reporting the greatest, at 48%.	World Bank

[2] To assess the level of agricultural digitalisation, several indicators can be used, including: Access to the internet and digital tools, which includes the availability of broadband internet, access to digital devices (computers, smartphones, etc.), and their use for agricultural activities; the use of digital technologies, which includes the use of farm management software, sensors for crop and soil monitoring, drones for observation and analysis, and other digital tools for decision-making; the adoption of digital agricultural practices, which refers to the integration of digital technologies into agricultural processes, such as the use of precision agriculture, automation of tasks, and the use of data to optimise yields and reduce inputs.

4.2 Methods

Based on frameworks provided by Sarkar *et al*. (2021), Ngo *et al*. (2022), Nian and Weiyu (2022), and Liang and Qiao (2025), this study estimated the following econometric model to assess empirically how agricultural digitalisation affects the high-quality development of agriculture, with modifications made to meet the goals of the study:

$$\mathrm{QAD_{it}} = f(AD_{it}AG_{it}GDP_{it}, TO_{it}\mathrm{EA_{it}}), \tag{1}$$

where QAD indicates high-quality agricultural development, AD is agricultural digitalisation, GDP denotes the gross domestic product per capita, AG refers to the agriculture value added, TO is trade openness and EA is employment in agriculture, representing energy consumption. Moreover, to avoid the issue of heterogeneity, we transformed Equations (1) into a logarithmic form, as follows:

$$\mathrm{LnQAD_{it}} = \beta_0 + \beta_1\mathrm{LnAD_{it}} + \beta_c\mathrm{Ln(Control_{it})} + \mu_t + \gamma_t + \varepsilon_{it}, \tag{2}$$

where i is the province and t denotes time; control refers to a set of provincial-level control variables; and ε_{it} is a random error term.

4.2.1 Cross-sectional dependence

According to Pesaran (2007), cross-sectional dependence (CD) testing has received a lot of attention lately in panel data analysis, since ignoring it can produce inaccurate and misleading results. We used the cross-sectional CD test to determine whether cross-sectional dependence occurs. The following is how the test is presented:

$$\mathrm{CD}\sqrt{\frac{2\mathrm{T}}{\mathrm{N(N-1)}}}\sum_{i=1}^{N-1}\sum_{j=j+i}^{N}\varphi_{ij}, \tag{3}$$

where N represents the number of cross-sectional units, T denotes the time period, and $\varphi_{ij}$is the pairwise correlation of the residuals.

4.2.2 Slope heterogeneity

Slope heterogeneity refers to the variation in slopes (or regression coefficients) across different groups or individuals in a dataset. In simpler terms, it means that the relationship between variables is not the same for everyone or every group being studied. This is a common issue in panel data analysis, where one has multiple observations for the same entities over time. The Swamy (1970) test requires panel data models where N is small relative to T, while the Pesaran and Yamagata (2008) test analyses slope homogeneity in large panels, where N and $T \to \infty$. For the $\tilde{\Delta}$ test, Pesaran and Yamagata (2008) proposed two main steps to be used to obtain the test statistic. First, the authors suggested computing the modified version of Swamy's test as:

$$\hat{\Delta}= \sqrt{N}.\frac{\mathrm{N^{-1}\gamma\%-K}}{2\sqrt{\mathrm{K}}}\&\hat{\Delta}_{\mathrm{adj}}= \sqrt{N}.\frac{\mathrm{N^{-1}\gamma\%-K}}{\sqrt{\frac{\mathrm{2K(T-K-1}}{\mathrm{T+1}}}} \tag{4}$$

4.2.3 Panel unit root tests

A unit root estimator was used in this study to assess the stationarity of the data. Even though panel data problems, like cross-sectional dependence, are common, they are addressed with an appropriate unit root estimate technique. Because these are more dependable and effective than other unit root approximations, like the ADF, Levin, Lin and Chu, among others, in terms of adjusting for the panel data challenge and producing more accurate results, this study used the cross-sectional Im, Pesaran and Shin (IPS) (i.e., CIPS) estimator created by Pesaran (2007). A component model for cross-sectional dependency analysis of inexplicable cross-sectional means was initially proposed by Pesaran in 2006. The CIPS and cross-sectional augmented Dickey Fuller (CADF) tests are statistical tests used in econometrics to determine if a panel dataset contains a unit root, a characteristic of time-series data that indicates non-stationarity. They are considered ‘second-generation’ tests, robust to cross-sectional dependence, a common issue in panel data analysis. The CIPS and CADF tests, which were first presented by Pesaran (2007), are the second-generation tests utilised in this work. The CIPS equation can be expressed as follows:

$$\Delta Z_{it} = \alpha_i + \beta_i Z_{i,t-1} + \rho_i T + \sum_{j=1}^{n} \gamma_{ij} \Delta Z_{i,t-1} + \varepsilon_{it}, \tag{5}$$

where ε_{it} stands for the deterministic components, γ for the level of significance, ε is the error term in the model, and $Z_{i,t-1}$ indicates respect variables. The cross-sectional augmented Dickey Fuller (CADF) can be obtained using the equation below:

$$\text{CIPS} = \frac{1}{N} \sum_{i=1}^{N} CADF_i \tag{6}$$

4.2.4 Panel co-integration

Westerlund (2007) proposed the cointegration test based on the error-correction model in Equation (7).

$$\Delta Y_{it} = \hat{\tau}_i d_t + \varphi_i \left(Y_{it-1} - \hat{\beta}_i X_{it-1} \right) + \sum_{j=1}^{k} \varphi_{ij} \Delta Y_{it-j} + \sum_{j=0}^{k} \gamma_{ij} \Delta X_{it-j} + \varepsilon_{it}, \tag{7}$$

where φ_i is the error correction term for the individual

$\alpha_i(y_{i,t_1\,\beta_i'} x_{i,t\_1})$.

In the equation, where the test establishes if this term equals zero, it indicates the absence of cointegration. Deviations from the long-run relationship may be remedied over time if the term is substantially different from zero.

The null hypothesis of the Westerlund (2007) test assumes a zero error-correction term (in a conditional error-correction specification of the panel data) and indicates no cointegration among the variables. Westerlund (2007) provided four statistics, namely Ga, Gt, Pa and Pt statistics. The Ga and Gt statistics help detect cointegration in one or more cross-sectional units, while the Pa and Pt statistics help detect cointegration in the whole panel. Their formulas are given as in Equation (8).

$$\begin{cases} G_t = N^{-1}\sum_{i-1}^{N}\frac{a}{SE(\alpha)} \\ G_t = N^{-1}\sum_{i-1}^{N}\frac{Ta}{\alpha(1)} \\ P_a = \frac{a}{SE(a)} \\ P_a = T_a \end{cases} \tag{8}$$

4.2.5 Panel estimation

This section explains the econometric procedure of estimating CS-ARDL and MMQR modelling for the asymmetrical impact of agricultural digitisation of the level of high-quality agricultural development in selected developed (G7) and developing (D7) countries.

- **MMQR method**

Koenker and Bassett Jr (1978) pioneered panel quantile regression, which uses explanatory parameter values to estimate dependent variance, as well as the conditional mean. Quantile regression produces efficient estimates when the dataset has irregular distributions. As a result of the non-normal distribution of the data, this research employed Machado and Santos Silva's (2019) novel method of moments quantile regression (MMQR). This unique approach examines the distributional as well as heterogeneous characteristics of quantile numbers (Sarkodie & Strezov 2019). A simple expression can be used to approximate the conditional quantile location-scale $QY(\varphi|K)$ variants:

$$Y_{it} = \gamma_i + \pi K_{it} + (\vartheta_i + \tau\grave{R}_{it})\mu_{it}, \tag{10}$$

where $p(\vartheta_i + \tau\grave{R}_{it}, t > 0) = 1$, and π, ϑ and ρ are the estimated parameters. The subscript (i) reflects the fixed effect described by γ_i and ϑ_i, where $i = 1,2,\ldots,n$, and *R* reflects the h-vector of standard elements in *K*, which exhibits a particular change with component $\mathbb{l}$, expressed as follows:

$$R_l = R_l(K), \quad l = 1,2,,,,,,,,,,,,h,$$

This prevents external behaviour and helps to stabilise the pieces. Equation (2) may therefore have the particular form shown below:

$$Q_y\left(\frac{\varphi}{K_{it}}\right) = \left(\gamma_i + \vartheta_i q(\varphi)\right) + \tau\grave{R}_{it}q(\varphi), \tag{11}$$

where Equation (11) shows that K_{it} is the vector of the response variable, which includes agricultural digitalisation (AD), agriculture value added (Ag), gross domestic product (GDP), trade openness (TO) and employment in agriculture (EA). For the empirical study, all of the variables described above are transformed into natural logarithms. The quantile distribution of the dependent variable (in this case, Yit, which captures high-quality agricultural development (QAD)) is conditioned on the location of the explanatory variables and Kit, as illustrated in the equation above.

The scalar coefficient, $-\gamma_i(\varphi) \equiv \gamma_i + \vartheta_i q(\varphi)$, indicates the fixed impact of t quantiles on i. Individual impact, on the other hand, does not affect the intercept. Due to the time-invariance of the parameters, the various effects are expected to fluctuate. Finally, $q(\varphi)$ signifies the quantiles' $(\varphi)th$ sample, of which this study assesses four, such as the 25th, then the 50th, the 75th, and the 90th. The quantile equation used in this study is as follows:

$$min_q \sum_i \sum_t \tau_F \left(K_{it} - \left(\boldsymbol{\vartheta_i} + \tau\grave{\mathrm{R}}_{\mathrm{it}}\right)\mathrm{q},\right. \quad (12)$$

where τ_F (S) = (F−1)AI{S≤0} + TSI{S>0} indicates the verification function. Nonetheless, the MMQR approach provides the estimated result for every regressor at a specific location and scale, but not for their causal link.

- **The cross-sectionally augmented autoregressive distributed lag (CS-ARDL)**

This approach is a statistical technique used in panel data analysis to investigate the relationships between variables, especially when there is a chance of heterogeneity (meaning that the relationships between variables may vary across those units) and cross-sectional dependence (meaning that the data points in various cross-sectional units are related). In order to address these problems, it expands on the conventional ARDL (autoregressive distributed lag) model by adding cross-sectional averages.

Equation (2) takes the following form, as shown in Equation (13), where α_i denotes the specific fixed effect of the country, and θ_i is known as a heterogenous co-efficient vector of the cross-section. R_{it}, is known as the regression vector, and μ_{it} is the error term, which is independent when the expected error is zero. Equation (11) is used as a dynamic panel ARDL.

$$\mathrm{Y_{it}} = \alpha_i + \theta_i R_{it} + \mu_{it} \quad (13)$$

Furthermore, $\mu_{it} = \rho_i Z_t + \varepsilon_{it}$, and $X_{it} = \delta_i + \xi \mathrm{Y_{it}} + \dot{\varphi}_i Z_t + \vartheta_{it}$, where $\mathrm{TEdu_{it}}$ is a common unobserved factor and μ_{it} is the error term. The main reason for the CS-ARDL is that the traditional panel ARDL technique has consistent results only if variables are integrated by level and first difference (Pesaran & Smith 1995; Pesaran *et al*. 1999).

By using the common correlated effects (CCE) method, the panel ARDL model was improved so that it could take into consideration the issue of cross-sectional dependency (Chudik & Pesaran, 2015) (see Equation (14)). After replacing the common unobserved factor with the cross-sectional average, the following equations were obtained (see Equation (16)). As a result, the cross-sectional dependence in μ_{it} is captured by the linear combination of cross-sectional averages of the dependent and independent variables, as in Equation (18). Under CS-ARDL, the panel ARDL specification of Equation (15) becomes:

$$\mathrm{TY_{it}} = \alpha_i + \sum_{k=1}^{p} \varphi_i\,, K\; T\; Y_{it-k} + \sum_{k=0}^{q} \grave{\beta}, X_{it-k} + \mu_{it} \quad (14)$$

$$\Delta TY_{it} = \alpha_i + \aleph_i\left(TY_{i,t-1} - \bar{\bar{\rho}}_i X_{i,t-1}\right) + \sum_{k=1}^{p-1} \varphi_{i;k}\, \Delta Y_{i,t-k} + \sum_{k=0}^{q-1} \beta_{i;k}\, \Delta X_{i,t-k} + \mu_{it} \quad (15)$$

$$\overline{\mathrm{TY}}_{\mathrm{t}} = \bar{\alpha} + \sum_{\mathrm{k=1}}^{\mathrm{p}} \overline{\varphi}_{\mathrm{k}}\, \overline{\mathrm{TY}}_{\mathrm{t-k}} + \sum_{\mathrm{k=0}}^{\mathrm{q}} \overline{\beta}_{\mathrm{k}}\, X_{t-k} + \bar{\rho} Z_t + \varepsilon_t \quad (16)$$

$$\mu_{it} = \rho_i Z_t + \varepsilon_{it}, \text{ and } X_{it} = \delta_i + \xi \mathrm{Y_{it}} + \dot{\varphi}_i Z_t + \vartheta_{it}$$
$$\overline{\mathrm{TY}}_{\mathrm{t}} = \bar{\alpha} + \sum_{\mathrm{k=1}}^{\mathrm{p}} \overline{\varphi}_{\mathrm{k}}\, \overline{\mathrm{TY}}_{\mathrm{t-k}} + \sum_{\mathrm{k=0}}^{\mathrm{q}} \overline{\beta}_{\mathrm{k}}\, \bar{X}_{t-k} + \bar{\rho} \bar{Z}_t + \varepsilon_t \quad (17)$$

$$\Delta TY_{it} = \alpha_i + \aleph_i\left(TY_{i,t-1} - \bar{\bar{\rho}}_i X_{i,t-1}\right) + \sum_{k=1}^{p-1} \varphi_{i;k}\, \Delta Y_{i,t-k} + \sum_{k=0}^{q-1} \beta_{i;k}\, \Delta X_{i,t-k}$$
$$\sum_{k=0}^{sz} \grave{p}_{i,k} \bar{A}_{t-k} + \sum_{k-1}^{p-1} \aleph\, \Delta TY_{it-k} + \sum_{k=0}^{q-1} \nexists_k \Delta \bar{X}_{t-k+}\, \varepsilon_{it} \quad (18)$$

Chudik and Pesaran (2015) listed the number of cross-sectional averages that were included. By doing this, the residuals are guaranteed to be cross-sectionally uncorrelated.

4.2.6 Hurlin and Dumitrescu's (2012) analysis of causality

This work uses the Dumitrescu and Hurlin (2012) causality test, which is robust, examines imbalanced panel data, and accounts for individual differences between nations (Serhat & Zafer 2017) to further investigate the causal relationship between economic activity, nighttime lighting, human capital and energy use. Equation (19) provides the empirical interpretation of the test, as follows:

$$Y_{it} = \alpha_i + \sum_{j=1}^{i} \pi_{ij} Y_{i(t-j)} + \sum_{j=1}^{i} \beta_{ij} X_{i(t-j)} + \varepsilon_{it}, \tag{19}$$

where x and y represent the number of observations, π_{ij} and β_{ij} represent the coefficient of the indicators, and Y_{it} represents the economic activity in Equation (19). The null hypothesis shows a coincidental link between the indicators and no causal relationship between the parameters.

5. Results

5.1 Results of basic statistics

Table 2 displays the preliminary statistics and correlation matrix for agricultural digitisation, the control variables and the quality development of agriculture. The table exhibits that multicollinearity is not an issue, since the correlation among variables is low. The correlation coefficients between the development of quality agriculture and other variables are significant. The coefficients of correlations point out that there are significant co-movements between agricultural digitisation and the development of quality agriculture (0.53). In addition, both the control of quality development of agriculture and other variables are positively and notably correlated in the sample of advanced economies. However, this does not conform to the situation in developing countries.

Table 2: Descriptive statistics and correlation matrix

	Developed countries						Developing countries					
	LnQAD	**LnAD**	**LnAG**	**LnGDP**	**LnTO**	**LnEA**	**LnQAD**	**LnAD**	**LnAG**	**LnGDP**	**LnTO**	**LnEA**
Mean	2.33	3.65	6.65	4.52	3.28	1.02	4.25	0.64	0.95	2.48	1.67	1.05
Std dev.	1.96	0.57	1.28	0.19	0.25	3.28	1.28	0.58	0.48	0.87	1.26	0.25
Skewness	0.56	0.84	2.33	0.28	0.11	.07	0.12	0.84	0.34	0.58	0.64	0.84
Kurtosis	0.78	0.25	0.68	1.25	2.36	0.32	0.84	.091	0.37	0.19	0.22	0.64
LnQAD	1						1					
LnAD	0.53	1					0.06	1				
LnAG	0.23	0.65	1				0.11	0.32	1			
LnGDP	0.45	0.66	0.78	1			0.22	0.41	0.42	1		
LnTO	0.48	.56	0.58	0.78	1		0.14	.11	0.37	0.52	1	
LnEA	0.26	0.45	0.49	0.51	0.53	1	0.08	0.18	0.19	0.43	0.25	1

Source: Output Result Eviews 12

Since the quality development of agriculture is highly correlated with agriculture value added, we checked the multicollinearity among the independent variables using the variance inflation factor (VIF) technique. Table 3 shows the results for multicollinearity. As a rule of thumb, if the VIF value of a variable is less than 10, then there is no multicollinearity problem.

Table 3: Multicollinearity statistics

Variables	Developed countries		Developing countries	
	Tolerance	VIF	Tolerance	VIF
LnQAD	0.236	1.032	0.156	1.236
LnAD	0.653	2.653	0.326	2.036
LnAG	0.258	0.653	0.648	3.659
LnGDP	0.956	1.256	0.456	2.256
LnTO	0.114	3.084	0.326	5.062
LnEA	0.023	2.032	0.148	1.205

Source: Output Result Eviews 12

Table 4 reports the results of the cross-sectional dependence tests (LM, LMS and CDP) and slope homogeneity tests ($\hat{\Delta}, \hat{\Delta}_{adj}$). It is evident from Table 4 that the cross-sectional dependence tests overwhelmingly show that the null hypothesis of no cross-sectional dependence is rejected in all the variables, with the implication being that there is cross-sectional dependence among the developed and developing countries. Therefore, shocks are transmitted across the developed and developing countries. Table 4 also shows that the null hypothesis of slope homogeneity is rejected in our data series. This is an indication that individuals in developed and developing countries possess unique economic peculiarities.

Table 4: Cross-sectional dependence and homogeneous test analysis

Variables	Developed countries					Developing countries				
	CD test results			S-H test results		CD test results			S-H test results	
	LM	LMS	CD_P	$\hat{\Delta}$	$\hat{\Delta}_{adj}$	LM	LMS	CDP	$\hat{\Delta}$	$\hat{\Delta}_{adj}$
LnQAD	150.2	11.2	-1.23	1.3	1.02	199.4	9.23	-2.45	2.45	2.02
LnAD	170.3	5.214	-2.45	2.45	2.33	187.2	2.65	-1.56	2.33	1.05
LnAG	218.4	4.025	-6.14	2.14	1.02	133.6	1.25	-1.49	3.25	2.58
LnGDP	127.5	1.236	-1.59	2.48	1.26	144.2	2.33	-6.33	4.15	4.02
LnTO	189.4	9.325	-1.44	3.22	3.02	150.4	2.88	-1.25	2.56	1.66
LnEA	122	8.876	-1.657	3.768	2.554	143	2.879	-1.76	2.654	1.778

Source: Output Result Eviews 12

Examining the integration order of the variables becomes crucial when cross-sectional dependence and homogeneous test analysis are confirmed. As a result, the CIPS and CADF panel unit root tests were also used in this investigation.

5.2 Results of panel unit root tests

Table 5 shows the results of the Pesaran CADF unit root test, applied to two cases in level form and in first differenced form. The table includes the Pesaran CADF test results in all the variables for all groups of countries.

Table 5: CADF panel unit root analysis

Variables	Developed countries				Developing countries			
	Level		1st diff.		Level		1st diff.	
	t-bar	Z(t-bar)	Z(t-bar)	t-bar	Z(t-bar)	t-bar	Z(t-bar)	t-bar
LnQAD	1.203	0.326	-3.256	-2.623	0.253	1.550	-2.336	-2.326
LnAD	0.326	0.548	-2.623	-2.658	0.145	1.114	-2.153	-6.325
LnAG	-1.203	0.256	-6.325*	-6.458	0.659	1.023	-2.956	-3.152
LnGDP	0.528	0.159	-2.652	-2.487	0.946	0.236	-2.485	-4.023
LnTO	-1.023	-1.034	-4.028	-3.124	1.551	0.485	-2.485	-2.156
LnEA	-1.358	-1.542	-6.458	-7.152	1.026	1.378	-3.225	-3.201

Note: * indicates significance at the 10% level
Source: Output Result Eviews 12

From Table 5, and according to the t-bar and Z(t-bar) statistics, these variables fail to reject the zero hypothesis for stability, thereby the variables are not stable on the surface; however, when the first differences were analysed, they were considered to be stable.

5.3 Results of the panel cointegration test

The study proceeded further to ascertain the presence of long-run cointegration amongst the variables using the Westerlund (2007) panel co-integration test, as the use of first-generation cointegration tests might generate biased outcomes. Thus, the researchers utilised the Westerlund test because it is robust in the presence of cross-sectional dependence and slope heterogeneity in the dataset, and estimated four statistics: two group mean tests (Gt, Ga) and two panel mean tests (Pt, Ga). Table 6 presents the results of the Westerlund cointegration test. As shown in Table 6, the null hypothesis of no cointegration was rejected at the 1% level of significance, indicating the presence of a long-run connection amongst the series in both developed and developing countries.

Table 6. Results of Westerlund panel cointegration test

	Developed countries			Developing countries		
Statistics	**Values**	**Z-value**	**Robust p-value**	**Values**	**Z-value**	**Robust p-value**
Gt	-4.526*	-3.254	0.021	-4.526*	-3.254	0.021
Ga	-11.326	-5.025	0.548	-11.326	-5.025	0.548
Pt	-6.574*	-2.254	0.014	-6.574*	-2.254	0.014
Pa	-18.251	-0.265	0.584	-18.251	-0.265	0.584

Note: * indicates significance at the 10% level
Source: Output Result Eviews 12

5.4 Results of panel estimation

After the validity of the cointegration between the variables was established, the study analysed the causal links between agricultural digitisation and high-quality agricultural development in the context of developed and developing countries by applying the estimation methods of CS-ARDL and MMQR modelling.

- **Method of moments quantile regression (MMQR) results**

Table 7 presents the findings derived from the MMQR approach.

Table 7: Results of method of moments quantile regression

	Developed countries						Developing countries					
	Location	**Scale**	**$Q^{0.25}$**	**$Q^{0.50}$**	**$Q^{0.75}$**	**$Q^{0.90}$**	**Location**	**Scale**	**$Q^{0.25}$**	**$Q^{0.50}$**	**$Q^{0.75}$**	**$Q^{0.90}$**
LnAD	0.789* [0.112]	-0.234 [0.090]	0.897* [0.127]	0.789* [0.294]	0.687* [0.213]	0.568* [0.254]	0.265* [0.078]	0.113 [0.194]	0.170* [0.065]	0.328* [0.194]	0.138* [0.234]	0.297* [0.345]
LnAG	0.236* [0.119]	-0.188 [0.198]	0.234* [0.298]	0.498* [0.089]	0.398* [0.149]	0.477* [0.177]	0.176* [0.345]	0.345 [0.287]	0.564* [0.326]	0.676* [0.209]	0.324* [0.198]	0.898* [0.287]
LnGDP	0.456 [0.342]	0.213 [0.129]	0.567* [0.113]	0.445* [0.108]	0.345* [0.345]	0.324* [0.289]	0.287* [0.276]	0.187 [0.190]	0.165* [0.678]	0.476* [0.554]	0.298* [0.325]	0.398* [0.213]
LnTO	0.378 [0.132]	0.209 [0.345]	0.234* [0.114]	0.345* [0.120]	0.312* [0.224]	0.456* [0.168]	0.123 [0.223]	0.124 [0.210]	0.223* [0.178]	0.213* [0.189]	0.345* [0.109]	0.742* [0.231]
LnEA	0.234 [0.098]	0.117 [0.289]	0.187* [0.192]	0.276* [0.335]	0.219* [0.118]	0.198* [0.168]	0.298* [0.345]	0.189 [0.119]	0.175* [0.869]	0.190* [0.098]	0.345* [0.435]	0.546* [0.435]
Constant	0.145* [0.178]	0.546 [0.265]	0.879* [0.167]	0.560* [0.241]	0.213* [0.234]	0.109* [0.387]	0.226* [0.098]	0.213 [0.554]	0.665* [0.435]	0.345* [0.087]	0.231* [0.176]	0.554* [0.178]

Notes: The dependent variable is LnQAD; *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively
Source: Output Result Eviews 12

In the case of developed countries: From the estimation of the results, the study noted that agricultural digitalisation (LnAD) is the only significant factor of high-quality agricultural development (LnQAD) among the selected variables, where a 1% increase leads to enhancing the high-quality agricultural development levels by 0.897% to 0.568% at a 1% level of significance. Also, the study found that agriculture value added (LnAG) was positively but significantly associated with high-quality agricultural development (LnQAD) in the medium and upper quantiles. On the other hand, the results demonstrate that economic growth (LnGDP), trade openness (LnTO) and employment in agriculture (LnEA) positively affected the high-quality agricultural development (LnQAD) in the developed countries. More specifically, an increase of 1% in both these variables substantially reduces the level of high-quality agricultural development (LnQAD) by 0.567% to 0.445%, 0.456% to 0.345% and 0.276% to 0.219%, respectively. These estimates are significant at the 10%, 5%, and 1% levels for LnGDP ($Q^{0.25}$ and $Q^{0.50}$), LnTO($Q^{0.50}$, $Q^{0.75}$, and $Q^{0.90}$) and LnTO ($Q^{0.50}$, $Q^{0.75}$). Further significance of these results could be captured from the significant estimates of the location.

In the case of developing countries: The study found that agricultural digitalisation (LnAD) was positively but insignificantly associated with high-quality agricultural development (LnQAD)in the medium and upper quantiles, where a 1% increase leads to enhancing the high-quality agricultural development (LnQAD) levels by 0.328% to 0.297% at a 1% level of significance. In addition, we observe that trade openness, economic growth (GDP), agriculture value added and employment in agriculture have a significant positive impact on high-quality agricultural development across all quantiles in developing countries. Furthermore, the degree of agricultural development is increased by 0.345% to 0.742%, 0.476% to 0.398%, 0.564% to 0.898% and 0.345% to 0.546%, respectively, for every 1% rise in these factors. For LnTO (Q0.75 and Q0.90), LnGDP (Q0.50 and Q0.90), LnAG (Q0.25, Q0.50 and Q0.90), and LnEA (Q0.75 and Q0.90), these estimates are significant at the 10%, 5%, and 1% levels. The location's substantial estimates could provide additional insight into the relevance of these findings.

- **Cross-sectional dependence autoregressive distributed lag model (CS-ARDL) results**

In this study, we address the problem of cross-sectional dependency in our panel time-series dataset by applying cross-sectional augmented-autoregressive distributed lags (CS-ARDL). Based on the Hausman specification test, we report only CS-ARDL (PMG) results. Under PMG, the long-run coefficients assume homogeneity, while error-correction adjustment and short-run coefficients follow heterogeneity. The cross-sectional ARDL approach is shown in Table 7 as a unique methodology used to investigate the relationship of selected variables. Furthermore, both developed and developing countries were selected as panels, because there is a strong disparity in the socio-economic development levels across developed and developing countries

In the case of developed countries, Table 8 shows that agricultural digitalisation (LnAD) positively and significantly contributes to high-quality agricultural development (LnQAD) in these countries both in the short run as well as in the long run. The coefficient of (LnAD) in the short run is 0.1254, while the (LnAD) coefficient in the long run is 0.6532.

Table 8: Results of cross-sectional autoregressive-distributed lag (CS-ARDL) in developed countries

	CS-ARDL	CS-ARDL	CS-ARDL	CS-ARDL
	Short-run estimates			
Error correction	-0.8235*** (-5.24)	-0.7581*** (-6.10)	-0.6804*** (-7.01)	-3.2150*** (-7.10)
ΔLnAD	0.1254* (1.47)	0.1147* (1.91)	0.1185* (1.46)	-6.0845 (-1.11)
ΔLnAG	1.2596*** (2.45)	1.3256*** (3.65)	1.5210*** (2.77)	0.2849 (0.12)
ΔLnGDP	1.3256*** (1.66)	1.5489*** (2.45)	1.5846*** (3.12)	0.8456 (0.58)
ΔLnTO		1.2563*** (1.22)	1.8496*** (1.84)	0.4963 (0.78)
ΔLnEA			0.6523*** (3.47)	0.2849*** (3.45)
ΔLnAD*LnAG				1.5462 (2.56)
	Long-run estimates			
LnAD	0.6532** (3.23)	0.3256*** (2.14)	0.5263** (2.15)	1.1526*** (4.23)
LnAG	14.1284** (3.23)	1.9856*** (2.14)	2.4415** (2.15)	2.5526** (4.23)
LnGDP	5.256** (2.12)	5.2361** (2.45)	4.2563** (3.54)	4.5623** (6.85)
LnTO		1.5869** (0.025)	1.8795** (0.052)	3.8026** (-0.07)
LnEA			2.1147 (1.25)	3.0895 (1.44)
LnAD*LnAG				0.4856*** (5.28)
Constant	10.1470*** (7.45)	12.4637*** (8.41)	8.1420*** (7.45)	-17.4521*** (-5.41)

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.
Source: Output Result Eviews 12

This shows that agricultural digitalisation (LnAD) significantly increases high-quality agricultural development (LnQAD), both in the long as well as in the short run. Still, the contribution of agricultural digitalisation (LnAD) to high-quality agricultural development (LnQADb) is higher in the long run. This shows that agricultural digitalisation (LnAD) is the right policy approach in developed countries to promote agricultural development. Similarly, it also shows that agricultural digitalisation in developed economies strongly connects them to the gross domestic product and has increased the productivity of agriculture. In the short run and long run, employment in agriculture and trade openness contribute positively and significantly to agricultural development. The consistent and highly significant impact of agricultural digitalisation on agricultural development in baseline and extended models once again confirms that agricultural digitalisation is a good policy tool to promote agricultural development in developed economies. The consistent and highly significant impact of agricultural value added, both in the short and long run, on agricultural development in baseline and extended models again reconfirms that strong agriculture value added is a good policy tool to promote agricultural development in developed countries.

Increased farm revenue, output diversification and market access are some ways that strong agriculture value added promotes agricultural growth. They accomplish this by turning unprocessed agricultural products into goods that consumers are ready to pay more for because of their additional convenience, flavour or nutritional content. Food security, livelihoods and rural economies can all benefit from this process. Therefore, high-quality agricultural development (LnQAD) is encouraged by agricultural value added. In our baseline model, agricultural development rises by 14.1284 units for every unit increase in agricultural value added. High-quality agricultural development (LnQAD) and the variables of interest appear to have a long-term relationship, as indicated by the negative and significant error-correction coefficients in the baseline and extended models in Table 8.

In the case of developing countries, Table 9 shows that agricultural digitalisation does not affect high-quality agricultural development in these countries both in the short run as well as in the long run. In the baseline model and extended models, the coefficient of agricultural digitalisation in the short run and the long run is insignificant. This finding shows that agricultural digitalisation has an insignificant effect on high-quality agricultural development both in the long run and short run. This means that agricultural digitalisation (LnAD) does not promote high-quality agricultural development (LnQAD) because of the lack of private capital accumulation and the underprivileged local industry in developing countries. The insignificant impact of agricultural digitalisation (LnAD) on high-quality agricultural development (LnQAD) also confirms that agricultural digitalisation (LnAD) in the developing economies is not very high due to the underprivileged agricultural industry.

Similarly, it also shows that agricultural digitalisation (LnAD) in developing economies does not strongly connect to the agricultural digitalisation (LnAD), and these economies have a problem with agricultural productivity. Other variables, such as trade openness and agriculture value added, contribute positively and significantly to agricultural development. Thus, public investment in agriculture (PUBI) crowds in agriculture value added in the short run as well as in the long run in emerging economies. Employment in agriculture does not affect agricultural development in the long run, but it contributes positively to agricultural development in the short run.

5.5 Results of panel causality test

To investigate the heterogeneous causal effect among the considered variables of both developed and developing countries, the panel DH causality test was applied in both panels. For developed countries, the results from the DH causality test are reported in Table 10. The results indicate that the majority of the variables, such as LnGDP-LnQAD, LnTO-LnQAD and LnEA-LnQAD, have one-way causality, while LnAD-LnQAD and LnAG-LnQAD have two-way causality. In the case of the developing countries panel, the majority of the variables have no causality. However, one-way causality was found in the LnAG-LnQAD, LnGDP-LnQAD, LnTO-LnQAD and FI-TOP.

Table 9: Results of cross-sectional autoregressive-distributed lag (CS-ARDL) in developed countries

	CS-ARDL	CS-ARDL	CS-ARDL	CS-ARDL
	Short-run estimates			
Error correction	-0.1655*** (-4.33)	-0.2435*** (-4.46)	-0.2134*** (-2.28)	-0.2314*** (-6.53)
ΔLnAD	0.2317 (0.45)	0.2234 (0.55)	0.1675 (1.09)	0.2243 (0.24)
ΔLnAG	0.3246 (0.88)	0.4356 (0.98)	0.5546 (1.32)	0.8790 (0.66)
ΔLnGDP	0.5145 (0.66)	0.0879 (0.09)	0.4536 (0.56)	0.4435 (0.14)
ΔLnTO		0.4456*** (3.66)	0.3487*** (3.23)	0.4590** (2.12)
ΔLnEA			0.3425*** (2.44)	0.4356*** (1.15)
ΔLnAD*LnAG				0.2435 (0.22)
	Long-run estimates			
LnAD	0.2234 (1.18)	0.1657 (0.88)	0.1123 (1.14)	0.2234*** (1.09)
LnAG	0.5567 (0.15)	0.4478*** (2.18)	0.2289*** (2.44)	0.3342*** (2.32)
LnGDP	0.345** (1.12)	0.378** (1.18)	0.289** (1.66)	0.345** (1.33)
LnTO		0.2675*** (1.12)	0.3980*** (1.93)	0.2213*** (1.86)
LnEA			0.3250 (0.99)	0.3916** (1.08)
LnAD*LnAG				0.4456*** (0.69)
Constant	7.0890*** (7.88)	4.3462*** (2.97)	8.7768*** (3.09)	12.0657*** (5.23)

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.
Source: Output Result Eviews 12

Table 10: Panel D-H causality test results

		Developed countries			**Developing countries**		
No	**Nullhypothesis(Ho)**	**Coef.**	**P value**	**Decision**	**Coef.**	**P value**	**Decision**
1	**LnQAD≠ LnAD**	7.98**	0.030	Causality	11.98	0.657	No causality
2	**LnAD ≠ LnQAD**	1.04*	0.000	Causality	6.70	0.721	No causality
3	**LnQAD≠ LnAG**	3.61*	0.000	Causality	2.91	0.274	No causality
4	**LnAG ≠ LnQAD**	1.87*	0.000	Causality	1.42	0.359	No causality
5	**LnQAD≠ LnGDP**	6.90	0.100	No causality	1.64	0.283	No causality
6	**LnGDP ≠ LnQAD**	7.45***	0.070	Causality	5.08***	0.06	Causality
7	**LnQAD≠ LnTO**	2.80	0.395	No causality	3.83	0.567	No causality
8	**LnTO ≠ LnQAD**	2.12*	0.000	Causality	1.37*	0.000	Causality
9	**LnQAD≠ LnEA**	1.04	0.287	No causality	2.04	0.436	No causality
10	**LnEA ≠ LnQAD**	1.89***	0.090	Causality	2.48**	0.02	Causality

Note: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.
Source: Output result Eviews 12

6. Discussion

We investigated the short- and the long-run impact of agricultural digitisation on agricultural development in developed and developing countries by applying a cross-sectional augmented-autoregressive distributed lag (CS-ARDL) and MMQR approach.

The results from the CS-ARDL, GMM and MMQR indicate a positively effect of agricultural digitisation on agricultural development in developed countries. In addition, our empirical analysis shows a positive and significant impact of trade openness, economic growth (GDP), agriculture value added and employment in agriculture on agricultural development in developed economies. This suggests that one of the most significant industries that strategically contributes to food security is agriculture. But, as the world's population grows, so will the demand for agri-food, necessitating a shift from conventional farming methods to smart agriculture practices, or agriculture 4.0. From the empirical perspective, the results are consistent with the existing studies of Izmailov (2019), Zhao and Xu (2021), Xie *et al*. (2022), Zhang *et al*. (2022), Quan *et al*. (2024) and Shamshiri *et al*. (2024), who provide evidence regarding the positive association between agricultural digitisation and agricultural development. For examples, through the use of digital technologies, agricultural digitisation is quickly changing farming methods in both the US and Canada. Automation, data analytics and precision agriculture are being used more frequently in both nations to boost productivity, sustainability and efficiency. They have, however, experienced particular possibilities and challenges throughout this shift. Also, agricultural digitisation investments and innovations are revolutionising the French agricultural sector as a result of agricultural digitisation, spearheaded by the France 2030 initiative. In Japan and the UK, agricultural digitisation refers to the use of technologies such as AI, drones and robotics to increase the sustainability and efficiency of farming. While the UK is investigating the potential of AI for predictive analytics to optimise farming operations, Japan is concentrating on combining IoT and AI-driven fertigation to overcome water shortages and increase output. The World Bank emphasises greater productivity, economic efficiency and environmental sustainability in order to assist high-quality agricultural development in industrialised nations. In order to meet the Sustainable Development Goals, this entails focusing on food system transformation, promoting climate-smart agriculture and digital technologies, mobilising capital for investment across the value chain, addressing structural inefficiencies, and enhancing smallholders' access to markets.

Agriculture is the foundation for large agricultural countries such as the developed countries. Since the countries' reform and opening up, agricultural development in developed countries has made great achievements. First, the supply of agricultural products and the ability to guarantee food security have been improved significantly, effectively meeting the growing consumption needs of the people. Second, breakthroughs have been made in the construction of agricultural infrastructure, resulting in a significant improvement in the ability to guarantee agricultural supply. Third, the ability to lead and support agricultural science and technology has been further strengthened, and quality and green agriculture have become the central themes of modern agriculture. Fourth, the agricultural industry pattern has shown new changes. Increased productivity and efficiency through precision farming, better environmental sustainability through resource optimisation, increased supply chain transparency and traceability, improved decision-making through data analysis, and contributions to the economic and social development of rural areas through higher incomes and new jobs are just a few of the added values of agricultural digitisation in developed nations.

The findings of a study by Abbasi *et al*. (2024) indicate that, in contrast to indoor farms (31%), open-air farms are often taken into consideration in research studies and that digital technologies like autonomous robotic systems, the internet of things, and machine learning are investigated extensively. Furthermore, the majority of use cases are still in the prototype stage, according to observations. At the technological and socioeconomic levels, possible obstacles to the digitisation of the agricultural sector have finally been recognised and categorised. This thorough analysis yields valuable data on the state of digital technology in agriculture now, as well as on potential future developments.

In developed countries, digital agriculture is expanding; for example, the AI in agriculture market is expected to rise from an anticipated $1.7 billion in 2023 to $4.7 billion by 2028. Benefits include reduced water consumption (up to 50%) via soil sensors, and a 70% to 90% reduction in herbicide use with precision sprayers, even though adoption rates vary. With 474 agri-tech companies based in Europe alone as of 2021, there is a significant amount of investment in agri-tech. For example, the adoption of digital agriculture is highest in the United States. It uses state-of-the-art precision farming technologies, government-backed programmes, and substantial agri-tech investments to propel improvements in smart farming solutions for both independent farms and huge agribusiness firms. The global market for digital agriculture is the second most important area of contemporary farming, after precision farming technology, and it is essential for raising agricultural productivity, sustainability and efficiency.

North America is embracing AI technology to improve productivity, resource management and decision-making processes in agriculture. AI applications include precision farming, remote sensing, crop monitoring, predictive analytics and automated farming systems. North American governments are implementing policies and initiatives to encourage AI adoption, such as financial incentives, research grants and legislative frameworks. A collaboration between the US and the EU that started in 2023 aims to improve agriculture, climate forecasting, emergency responses and the electrical grid. The Asia Pacific region is expected to show the highest compound annual growth rate (CAGR) due to population growth, climate change impacts, and water scarcity concerns. The FAO's 'Global Action on Green Development of Special Agricultural Products' initiative is also expected to boost market growth.

One of the important results revealed by this study is that agricultural digitisation does not significantly impact agricultural development in developing countries in the short or the long run. This is due to a lack of investment and innovation in agricultural digitisation, as well as poor global supply chains. While developed countries typically have more advanced digital infrastructure and greater resources to support digital transformation in agriculture, developing countries face significant challenges related to digital agriculture, such as limited access to technology and skills, funding constraints and inadequate infrastructure. Other variables, such as agriculture value added, gross domestic product, trade openness and employment in agriculture positively and significantly contribute to agricultural development. Although the value added of agriculture as a percentage of GDP is often larger in developing nations than in industrialised ones, this share of GDP tends to decline as economies grow. The reason for this drop is that other industries, such as manufacturing and services, have been growing faster than agriculture. Even while the direct economic contribution of agriculture to GDP is declining, it is still an important sector, especially for environmental sustainability and food security.

Finally, through increased productivity, better resource allocation and market connections, agricultural digitisation can dramatically raise value added in underdeveloped nations. In order to access financial services and maximise farming methods, this shift entails implementing digital technology, such as data analytics, mobile banking for farmers and precision agriculture instruments. But digitalisation in agriculture faces several obstacles in developing nations, especially when it comes to the value that agriculture adds. Digital technologies have the potential to boost efficiency and productivity, but their use is hindered by challenges with affordability, digital literacy and infrastructure. Concerns about data protection and the digital divide also make things more difficult.

7. Conclusions

We investigated the short- and the long-run impact of agricultural digitalisation and control variables on the high-quality agricultural development in the sample of developed and developing countries. Our study contributes to the existing literature by investigating the dynamic links between agricultural digitalisation, control variables and the high-quality agricultural development using the innovative method of moments quantile regression (MMQR). Due to the strong presence of cross-sectional dependency and unit roots in our series, we applied a cross-sectional augmented-autoregressive distributed lags (CS-ARDL) approach. This approach was also selected for its ability to assess the heterogeneous effects of agricultural digitalisation and control variables on high-quality agricultural development across various quantiles. As a result, the study provides new insights into the symmetric impact of agricultural digitalisation on agricultural development within the context of developed and developing countries.

After the validity of the cointegration between the variables was shown, our empirical analysis indicates a positive and significant impact of agricultural digitalisation on agricultural development for developed economies. In contrast, our analysis found an inconclusive impact of agricultural digitalisation on high-quality agricultural development in the context of developing countries. Poor institutions hamper capital formation by bringing instability to the system and by increasing the transaction costs. Agricultural digitalisation and agriculture value added also contribute positively to high-quality agricultural development in developed countries in the long run. The results on the sectoral level show that agricultural digitalisation strongly increases agricultural development in developed countries, and vice versa in developing countries due to different economic structures and economic policies in the two types of economies.

The results obtained via the MMQR technique, which was used due to asymmetrical data distribution. are reported here. From the estimation of the results, the study noted that agricultural digitalisation was the only significant factor of high-quality agricultural development among the selected variables. Also, the study found that agricultural value added was positively associated with agricultural development in the medium and upper quantiles. On the other hand, the results demonstrate that gross domestic product, trade openness and employment in agriculture adversely affect agricultural development in the developed economies. These estimates are significant at the 10%, 5% and 1% levels (Q0.50, Q0.75 and Q0.90). The further significance of these results could be captured from the significant estimates of the location.

From the estimation of the results, on the other hand, the study found that agricultural digitalisation was the only insignificant factor of high-quality agricultural development among the selected variables. Also, the study found that agriculture value added, gross domestic product, trade openness and employment in agriculture were positively but insignificantly associated with high-quality agricultural development in the medium and upper quantiles in the developing economies.

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