

Effects of digital economy-driven Chinese-style agricultural modernisation--based on analysis of mediating effects and spatial spillovers

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ABSTRACT

Agricultural modernisation is central to rural development and long-term food security, yet its pathways remain uneven across space. In the context of China's rapid digital expansion, this study examines how the digital economy reshapes agricultural modernisation and rural transformation. Using panel data for 30 Chinese provinces from 2014 to 2023, we construct comprehensive indices of the digital economy and agricultural modernisation and apply fixed-effects and spatial econometric models to analyse direct effects, mediating mechanisms, and spatial spillovers. The results show that the digital economy significantly advances agricultural modernisation by enhancing productivity, resilience, and product quality. Technological innovation acts as an important mediating channel, amplifying the modernising effects of digitalisation. We also identify strong spatial spillover effects, indicating that digital economy development in one region can promote agricultural modernisation in neighboring regions. These effects are spatially heterogeneous, with stronger impacts observed in western provinces and major grain-producing and production–marketing balance areas. By revealing the mechanisms and spatial dynamics through which the digital economy influences agriculture, this study contributes to debates on digitalisation, rural inequality, and uneven rural transformation, and offers policy-relevant insights for digitally enabled rural development in China and other emerging economies.

1. Introduction

The rapid advancement of new-generation information technologies, including big data, cloud computing, mobile payments, e-commerce, and Artificial Intelligence (AI), has fundamentally reshaped contemporary economic systems. Collectively described as the digital economy, these technology-enabled activities now constitute a major driver of global economic growth and structural transformation (Heeks et al., 2024). The digital economy is widely understood to encompass economic activities centred on the production, distribution, and use of digital technologies (Shao and Wang, 2025). Nowhere is this transformation more evident than in China, where the digital economy reached 53.9 trillion yuan in 2023, accounting for nearly 43% of national GDP (China Academy of Information and Communications Technology, 2024). Sustained growth in China's Digital Development Index, alongside rapid expansion in computing power, data production,

and digital infrastructure, highlights the strategic importance of the digital economy in shaping China's development trajectory (National Data Administration, 2024).

At the same time, China faces persistent challenges in the agricultural and rural sectors. Agricultural modernisation, commonly understood as the transformation of agriculture through mechanization, technological innovation, capital intensification, and institutional change (Dibua, 2002), is widely recognised as a prerequisite for sustainable rural development and national food security. Within the framework of “Chinese-style modernisation”, agricultural modernisation is positioned as a foundational pillar of national development, reflecting the country's demographic scale, resource constraints, and regional diversity. Unlike linear modernisation pathways observed in some developed economies, Chinese agricultural modernisation seeks to balance traditional smallholder farming structures with modern technologies, market institutions, and national strategies. A defining feature

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of this approach is the growing integration of the digital economy into agriculture, manifested in rural e-commerce platforms, smart logistics systems, digital finance, and data-enabled production and management practices.

From a policy perspective, agricultural modernisation is not merely an economic objective but a strategic imperative. The State Council of the People's Republic of China emphasises food security as a core component of national security, underscoring the need to ensure stable supplies of essential agricultural products, particularly grain. Against this backdrop, the digital economy has been increasingly viewed as a potential catalyst for overcoming long-standing constraints in agriculture, such as low productivity, fragmented supply chains, and persistent rural–urban disparities. This raises a central and timely question: to what extent, and through what mechanisms, can the digital economy contribute to agricultural modernisation in China?

Existing scholarship has made important progress in examining the relationship between the digital economy and China's rural development. Prior studies have focused on issues such as the urban–rural income gap (Chen and Wu, 2021), rural revitalisation strategies (He et al., 2022), and conceptual or policy-oriented models for integrating the digital economy with agriculture and rural economies (Wen and Chen, 2020). More recent research has begun to explore the enabling role of digital technologies in agricultural development (Fu and Li, 2023). However, three significant gaps remain. First, much of the literature treats the digital economy as a broad aggregate phenomenon, offering limited insight into the specific mechanisms through which it influences agricultural modernisation. Second, empirical analyses often rely on static or non-spatial approaches, overlooking the inherently spatial nature of both digital infrastructure and agricultural development. Third, despite China's regional heterogeneity, there is a lack of spatial quantitative evidence examining whether and how the digital economy generates spillover effects that shape agricultural modernisation across regions. These gaps limit our understanding of the role of the digital economy in transforming agriculture within a large, spatially diverse developing country.

This study seeks to address these gaps by systematically analysing the relationship between the digital economy and agricultural modernisation in China from a spatial perspective. Specifically, the study pursues three objectives. First, it constructs comprehensive and theoretically grounded evaluation index systems to measure the development levels of both the digital economy and agricultural modernisation. Second, it empirically examines the direct and indirect mechanisms through which the digital economy influences agricultural modernisation. Third, it employs spatial econometric models to investigate whether and how the digital economy generates spatial spillover effects in agricultural modernisation across regions.

Guided by these objectives, the study addresses the following research questions:

- (1) How does the development of the digital economy affect agricultural modernisation in China?
- (2) Through what mechanisms does the digital economy promote agricultural modernisation?
- (3) Do spatial spillover effects exist in the relationship between the digital economy and agricultural modernisation, and if so, how do they vary across regions?

The contributions of this study are twofold. Theoretically, it integrates research on the digital economy with agricultural modernisation within a unified analytical framework, extending perspectives from technology diffusion and spatial economics to the context of rural and agricultural transformation. By explicitly examining direct, indirect, and spatial spillover effects, the study deepens understanding of how digital technologies reshape agricultural systems across regions. Methodologically, the study develops an innovative indicator system and applies entropy weight–TOPSIS and entropy weight–grey correlation analysis to

measure development levels more rigorously than in much of the existing literature. Combined with spatial econometric modelling, this approach provides robust empirical evidence to support both academic inquiry and policy formulation.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and develops the theoretical framework. Section 3 describes the empirical research design and methodology. Section 4 presents the empirical results. Section 5 provides further analysis and discussion. Finally, Section 6 concludes with key findings and policy implications.

2. Literature review

2.1. Digital economy

The economic impacts of the digital economy have been widely examined at national, regional, and industrial levels, with a general consensus that digitalisation enhances productivity and facilitates structural transformation. Early studies in advanced economies established that information and communication technologies (ICT), when combined with organisational change and skills upgrading, significantly contribute to productivity growth (Brynjolfsson and Hitt, 2000; Oliner and Sichel, 2000). Subsequent research has extended this perspective by highlighting the role of digital infrastructure and asset ownership in shaping broader economic outcomes (Bridgman et al., 2024). At the industrial level, digital technologies are consistently found to support industrial upgrading and the modernisation of traditional sectors (Audretsch et al., 2015; Carlisle and Kunc, 2013).

More recently, attention has shifted towards China, where rapid digital expansion provides a valuable context for examining development impacts in emerging economies. Existing studies largely report positive effects, including improvements in firm productivity, accelerated digital transformation of traditional industries, and aggregate economic growth (Jiang and Sun, 2020; Chen et al., 2022). Provincial-level evidence further suggests that the digital economy can promote rural industrial revitalisation and enhance regional productivity (Wang et al., 2025; Liu and Lin, 2025).

However, the literature remains limited in addressing spatially uneven outcomes, particularly across rural and peripheral regions. Most studies focus on average effects or urban- and province-level aggregates, offering limited insight into how digital economy benefits are differentiated across rural contexts with varying infrastructure, institutional capacity, and human capital endowments. Moreover, the mechanisms through which digitalisation reshapes rural economic structures remain underexplored. Responding to these gaps, this study examines the regional differences of the digital economy with particular attention to rural development, thereby contributing to debates on digitalisation, spatial inequality, and rural transformation.

2.2. Agricultural modernisation

Existing literature on agricultural modernisation has largely drawn on the experiences of developed economies, focusing on identifying key drivers and institutional arrangements underpinning productivity growth and technological change. Studies based on the U.S. model highlight the central role of institutional innovation in facilitating agricultural technological progress (Jiang and Song, 2008), while others emphasise the importance of farmer education and training in supporting modernisation processes (Zhang et al., 2016). Complementary research points to the contributions of mechanization (Sasaki, 2004), human capital and agricultural insurance (Goodwin, 2001), and information and communication technologies (Rehman et al., 2016). Taken together, this body of work converges on a set of enabling factors, such as institutions, skills, capital, and technology, which are widely regarded as foundational to agricultural modernisation.

In the Chinese context, scholarly attention has increasingly shifted

towards conceptualising and operationalising a distinct pathway of “Chinese-style” agricultural modernisation, reflecting the country's unique rural institutions and development trajectory. Recent studies propose multidimensional measurement frameworks incorporating production inputs, management practices, quality, and efficiency (Meng et al., 2023; An and Xin, 2020). Others situate agricultural modernisation within broader processes of industrialization, urbanisation, and informatisation, emphasising its role in advancing rural livelihoods and common prosperity (Tu, 2023). Environmental sustainability has also emerged as a key concern, with scholars highlighting the need to embed ecological agriculture and green transformation within modernisation strategies (Wang and Shi, 2023).

Despite these advances, existing research remains predominantly framework- and indicator-driven, offering limited insight into how agricultural modernisation is experienced and differentiated across rural regions. In particular, the interactions between modernisation pathways, spatial inequality, and rural socio-economic transformation are underexplored. Addressing these gaps requires greater attention to regional variation and the lived realities of rural development, which this study seeks to contribute to.

2.3. Digital economy empowered agricultural modernisation

The digital economy has increasingly been framed as a transformative force in agricultural modernisation, marking a shift from input-intensive production towards knowledge- and data-driven farming systems. Digital technologies, including the Internet of Things (IoT), big data, and AI, are reshaping agricultural production by embedding information flows and analytical capacity into traditional farming practices (Leng, 2022). Existing studies position digitalisation as a core driver of agricultural modernisation, enabling productivity gains while potentially decoupling growth from resource intensity and environmental degradation (Basso and Antle, 2020; Schroeder et al., 2022).

At the farm and value-chain levels, research highlights the role of smart farming technologies, data-enabled decision-making, and digital platforms in improving input efficiency, enhancing yield stability, and strengthening coordination among rural actors (Runck et al., 2022). Digital advisory services and mobile-based extension systems have been shown to reduce information asymmetries, particularly for smallholder farmers, thereby improving access to agronomic knowledge and markets (Birner et al., 2021). Empirical evidence from early-adopting regions suggests that these technologies can generate measurable productivity gains and improve market participation (Chandio et al., 2024). In China, the rapid expansion of rural e-commerce and digital traceability systems illustrates how digitalisation is restructuring agricultural markets, expanding market access, and upgrading product quality standards.

However, the literature also points to potential constraints that limit the inclusiveness of digitally enabled agricultural modernisation. Successful digital transformation depends on adequate digital infrastructure, institutional support, and human capital, which remain unevenly distributed across rural regions. Despite policy initiatives such as China's “Internet + Agriculture” strategy, disparities in digital literacy, particularly among older farmers, high adoption costs, and uneven infrastructure coverage continue to shape differentiated outcomes (Granado-Díaz et al., 2024; McCampbell et al., 2022). These challenges raise concerns that digitalisation may reinforce existing spatial and social inequalities within rural areas rather than alleviate them.

Overall, while existing research confirms the transformative potential of the digital economy for agricultural modernisation, important gaps remain. In particular, there is limited empirical evidence on the spatially uneven impacts of digitalisation across rural regions, insufficient analysis of the mechanisms linking digital economy development to broader processes of rural transformation, and a lack of integrative assessments of how digital adoption reshapes rural livelihoods beyond productivity outcomes. Addressing these gaps is essential for

understanding the role of digitalisation in rural development. This study responds by examining China's experience of digital economy-driven agricultural modernisation, with explicit attention to regional differentiation and rural development implications.

3. Theoretical analysis and hypotheses development

3.1. Theoretical foundation

3.1.1. Induced technological change

The theory is a concept developed by the Japanese agricultural development economist, Yujiro Hayami, and the American agricultural development economist, Vernon W. Ruttan, to illustrate the path of agricultural development and technological progress. According to Yujiro Hayami and Vernon W. Ruttan, the growth of agricultural productivity depends on the continuous progress of modern agricultural technology, which takes two forms, one mechanical and the other biochemical. The path of technological progress chosen by a country depends on the state of the country's resource endowment and the dynamic growth of demand for its products, so technological progress is considered to be endogenous, the result of the action of the market mechanism, rather than determined by external factors of the progress of scientific and technological knowledge. Based on this theory, this paper introduces technological innovation as a mediating variable to analyse its mediating role in the process of digital economy affecting agricultural modernisation.

The digital economy empowers agricultural modernisation through technological innovation. On the one hand, the development of the digital economy facilitates the dissemination and exchange of information, and can promote the exchange and interaction of knowledge in the technological innovation region. And the development dividend brought by the digital economy can attract more innovative subjects to participate in technological innovation activities, which has a positive impact on technological innovation, not only that, the digital economy can improve the efficiency of technological innovation. Digital economy promotes the exchange of information resources, which can reduce the resistance in the process of technological innovation and improve the circulation efficiency of innovation resources. On the other hand, technological innovation empowers agricultural modernisation. Technological innovation can enhance production efficiency and improve the level of agricultural production. For example, the innovation of agricultural planting technology can plant crops according to local conditions and optimize the allocation of agricultural resources; through the innovation of crop varieties and the cultivation of new varieties with excellent traits, such as resistance to pests and diseases, drought, salinity and alkalinity, it can reduce the negative impacts of natural disasters on agriculture; technological innovation can also improve the quality of agricultural products. Innovations in seed treatment technology, such as seed coating and seed treatment agents, can effectively increase the germination rate of seeds, enhance their adaptability to different environments and their nutrient uptake, and improve the quality of crops.

3.1.2. Transforming traditional agriculture

The theory, developed by the American economist Theodore Schultz, distinguishes between traditional and modern agriculture. Schultz defined traditional agriculture as relying exclusively on production factors that farmers have used for generations, whereas modern agriculture incorporates modern technologies, means of production and management methods. He considered traditional agriculture as a state of economic equilibrium in which the state of agricultural technology, preferences and incentives to obtain income remain unchanged, making it difficult for traditional agriculture to drive economic growth. The key to transforming traditional agriculture is the introduction of modern agriculture factors, the widespread adoption of advanced science and technology, professionalization and socialization of forms of agricultural production, which will lead to the further development of

agriculture.

In this paper, the theory is used throughout the construction of the indicator system of agricultural modernisation, focusing on the inputs of agricultural production factors and the improvement of agricultural productivity in the process of transforming traditional agriculture. Drawing from the theories of induced technical change and transforming traditional agriculture, a theoretical framework is constructed and presented in Fig. 1 and Fig. 2.

3.2. Direct mechanisms of the digital economy driving the modernisation of agriculture

The wide application of smart devices and technology can reduce agricultural costs and improve agricultural production efficiency (see Fig. 2). For instance, the use of artificial intelligence technology to accurately detect crop pests and diseases can lower pesticide expenses (Wang and Li, 2023); utilising drone technology to spray pesticides can reduce labor cost (Ayamga et al., 2021); leveraging the Beidou satellite navigation system allows agricultural machinery perform precise tasks based on accurate positioning information (Huang et al., 2015); and implementing autonomous driving technology for agricultural machinery not only eases labour burden on vulnerable farmers but also increases the efficiency of mechanical operations (Ko et al., 2022).

The popularization of network infrastructure can optimize the agricultural structure and promote the modernisation of agricultural management. By applying 5G networks to agricultural management and operation, farmers can realize remote monitoring of their farmland, and they can check the temperature and humidity of crops and other information on their cell phones at any time, so that they can adjust their management plans in a timely manner. In addition, the popularization of the network can also be used to adjust the planting structure in a timely manner according to the agricultural subsidy policy and insurance policy, and with the support of the Internet, the de-intermediation makes the market more transparent, which helps agricultural entities to adjust the planting structure in a timely manner according to the market information (Liang, 2022).

The use of big data can realize the safety traceability of agricultural products and guarantee the quality of agricultural products (Liang, 2022). The quality and safety of agricultural products is an important link in the modernisation of agriculture, and with the frequent occurrence of food safety problems, the quality and safety of agricultural products receives increasing attention. Relying on big data, the process of agricultural products from production, transportation, warehousing

to sales is entered into the two-dimensional code, so as to build a traceability system for the quality and safety of agricultural products (Zhang et al., 2021). Consumers or regulators only need to scan the barcode or two-dimensional code to understand the origin of agricultural products, processing, fertilizers and pesticides to comply with standards and other information, so as to achieve quality traceability, product monitoring. Fleming et al. (2018) pointed out that the impact of big data on modern agriculture is huge, and it is a "major revolution" that will benefit all farmers.

Furthermore, the promotion of digital inclusive finance significantly enhances agricultural economic resilience (Gao et al., 2024). Digital inclusive finance, a new financial model, realizes inclusive, fair and progressive financial services by means of financial technology. As the combination of digital economy and finance, digital inclusive finance provides convenient, efficient, safe and low-cost financial services for rural areas that are difficult to be covered by traditional financial services. This means has expanded the coverage of financial services and made an innovative contribution to "inclusive" financial services for farmers and small and micro agricultural enterprises (Huang and Azman, 2023).

Based on the findings from aforementioned literature, this paper proposes research **hypothesis 1**: The digital economy has a positive driving effect on agricultural modernisation.

3.3. Indirect mechanisms of digital economy-driven agricultural modernisation

On the one hand, the development of digital economy effectively promotes technological innovation Fig. 3. First, the digital economy creates an innovative environment for technological innovation. The development of digital economy facilitates the dissemination and exchange of information, which can promote the exchange and interaction of knowledge in the technological innovation region (Hjaltadóttir et al., 2020). Moreover, the development dividend brought by the digital economy can attract more innovative subjects to participate in technological innovation activities, which has a positive impact on technological innovation; secondly, digital products can enhance the technological innovation ability; ICT industry, as a typical industry in the field of digital economy, can directly enhance the technological innovation ability of its related products, and the digital products, as an intermediary product, can be applied to other industries, which indirectly leads to new technological innovation. The application of digital products as intermediate products to other industries has indirectly led

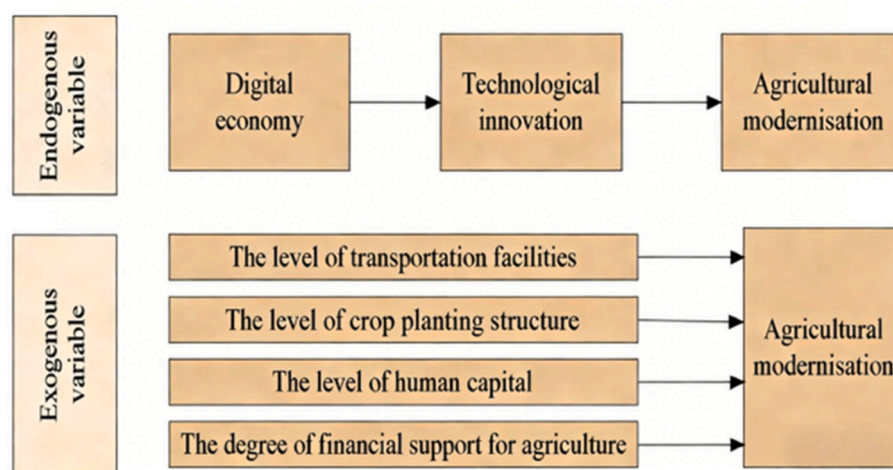


Fig. 1. Theoretical framework.

*Digital economy as an endogenous variable; Agricultural modernisation as an exogenous variable; Technological innovation as a mediating variable; The level of transportation facilities, the level of foreign trade, the level of human capital and the degree of financial support for agriculture are control variables.

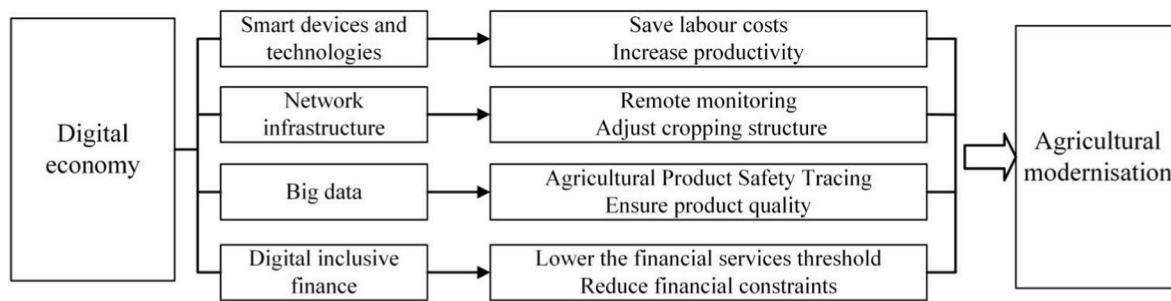


Fig. 2. Schematic representation of direct effects.

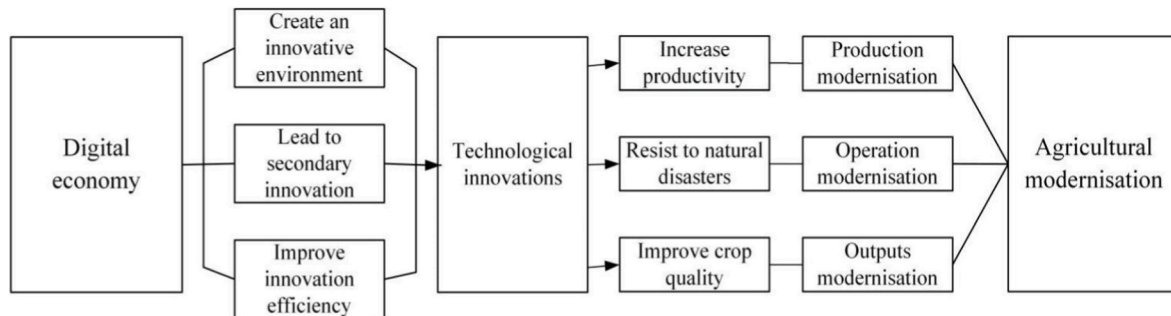


Fig. 3. Schematic representation of indirect effect of technological innovation.

to secondary innovation (Song, 2020); finally, the digital economy can improve the efficiency of technological innovation. Digital economy promotes the exchange of information resources and fosters collaborative, which can reduce the resistance in the process of technological innovation and improve the circulation efficiency of innovation resources (Fang and Liu, 2024). Utilizing digital technology, innovation subjects can accurately and quickly locate innovation resources and improve the search and matching efficiency of innovation resources.

On the other hand, technological innovation empowers agricultural modernisation. First of all, technological innovation can enhance production efficiency (Ugur et al., 2018) and improve the level of agricultural production (Anderson, 2023). The innovation of agricultural machinery technology can enhance the efficiency of agricultural mechanization, the innovation of land fertilization technology can enhance soil fertility and increase crop output, and the innovation of agricultural planting technology can plant crops according to local conditions and optimize the allocation of agricultural resources; secondly, technological innovation can enhance the ability to resist natural disasters. Through the innovation of crop varieties and the cultivation of new varieties with excellent traits such as resistance to pests and diseases, salinity and alkali, the negative impact of natural disasters on agriculture can be reduced; finally, technological innovation can improve the quality of agricultural products (Zhang et al., 2022). Innovations in seed treatment technology, such as seed coating and seed treatment agents, can effectively improve the germination rate of seeds, enhance their adaptability to different environments and nutrient uptake, and improve the quality of crops. Liu et al. (2024) stress that strengthening the quality and safety of agricultural products through technological innovation brought by digital transformation is the key to enhancing the competitive advantage of agricultural products and achieving high-quality agricultural development.

Based on these discussions, this paper proposes research **hypothesis 2**: The digital economy drives agricultural modernisation through technological innovation.

3.4. Spatial spillovers from digital economy-driven agricultural modernisation

The first element considered is a self-attribute “cross-regional expansion and extension”, as shown in Fig. 4 The digital economy and agricultural modernisation levels vary across regions, creating opportunities for the digital economy to have a spillover effect on agricultural modernisation in the surrounding areas. Moreover, the digital economy itself has expansiveness and extensibility, which promotes the cross-regional expansion and extension of the digital economy (Fu and Li, 2023). Secondly, the digital economy takes network information and data resources as the key elements, which have the characteristic of sharing. This kind of network information sharability can overcome spatial distances, reduce information asymmetry, maximize resource integration and build “digital bridges” between regions, thus promoting cross-regional factor (Ren et al., 2021). Thirdly, Digital transformation in agriculture has spillover effects. Digital transformation in agriculture means the deep penetration of the digital economy into agriculture, which could play a leading role in the upgrading of modern agriculture. Successful cases, as well as demonstration zones and demonstration bases of agricultural digital transformation, provide valuable experiences and advanced practices for surrounding areas, playing a leading and exemplary role. Finally, the spillover effect of the digital economy is also reflected in the spillover of talent and knowledge. Communication infrastructure mainly refers to group communication applications, social media, mobile devices and other network equipment facilities (Schmidt et al., 2013). They have a positive spatial spillover effect, which can promote the diffusion of knowledge and technology (Li and Wang, 2018). Moreover, the inter-regional mobility of agricultural technology talents can promote the exchange and interaction of agricultural technology knowledge between regions, thus driving the progress of agricultural technology in other regions and generating knowledge and technology spillover effects.

Based on these discussions, this paper proposes research **hypothesis 3**: digital economy-driven agricultural modernisation has spatial spillover effects.

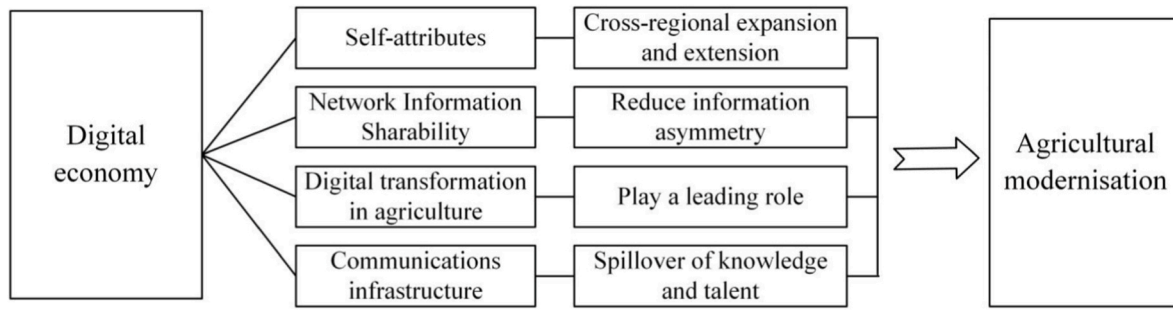


Fig. 4. Schematic representation of spatial spillover effects.

4. Methodology

4.1. Sample data

In this paper, we select the panel data of 30 provinces and cities in China except Hong Kong, Macao, Taiwan and Tibet from 2014 to 2023. The data come from *China Statistical Yearbook*, *China Statistical Yearbook on Science and Technology*, *China Energy Statistical Yearbook*, *China Rural Statistical Yearbook*, *China Agriculture Yearbook*, *China Rural Statistical Yearbook on Environment*, *China Insurance Yearbook* and Peking University Digital Inclusive Finance Index.

4.2. Definition of variables and models

4.2.1. Mathematical models

In this paper, the following model is constructed for the benchmark regression analysis:

$$Agr_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 Controls_{it} + \mu_{it} + \varepsilon_{it} \quad (1)$$

Drawing on the method of Jiang (2022) to examine the mediating effect of digital economy-driven agricultural modernisation, the following mediating effect model is constructed:

$$Tec_{it} = \beta_0 + \beta_1 Dig_{it} + \beta_2 Controls_{it} + \varphi_{it} + \varepsilon_{it} \quad (2)$$

Equation (2) is used to test the effect of digital economy on the mediating variable.

i : the region i ;
 t : the year t ;
 Dig_{it} : digital economy in year t and in region i ;
 Agr_{it} : agricultural modernisation in year t and in region i ;
 Tra : the level of transportation facilities;
 Hum : the level of human capital;
 Gov : the degree of financial support for agriculture;
 Str : the proportion of the area planted with food crops to total sown crop area;

$Controls_{it}$: the control variables in t in i , including the level of transportation facilities (Tra), the level of human capital (Hum), the level of financial support for agriculture (Gov), and the proportion of the area planted with food crops to total sown crop area (Str);

Tec_{it} : the mediating variable, indicating the level of technological innovation in year t and in region i ;

L_Dig : lagged one period of the digital economy;

Pos_Int : the interaction term between the number of post offices per million people in each region in 1984 and the number of Internet users in the country in the previous year;

μ_{it}/φ_{it} : the time-individual fixed effects;

ε_{it} : the random perturbation terms.

4.2.2. Digital economy

Referring to the digital economy indicator system constructed by Zhang and Jiao (2017) and Liu et al. (2020), based on which the digital

penetration degree is taken as a first-level indicator alone, the digital economy development level indicator system is constructed from four aspects, namely, digital infrastructure, digital industrialization, industrial digitization and digital penetration, and the indicator system includes a total of 12 s-level indicators, as shown in Table 1. Digital infrastructure encompasses the foundational technologies and systems that enable the functioning of digital services, activities and applications within a economy. Digital industrialization involves the research and development, production and application of digital technologies with information technology (IT) and communication technology (ICT) as the core. Industrial digitalisation refers to the transformation and upgrading of traditional industries through the introduction of digital technologies to improve production efficiency, optimize management processes and innovate business models. Digital penetration measures the degree to which digital technologies, services or devices have been adopted and integrated within an industry or a geographic area.

Referring to the study by Li and Wang (2022), this paper uses the entropy weight-TOPSIS method to measure the level of digital economic development. The specific steps are shown in the appendix.

4.2.3. Agricultural modernisation

According to Xin and Jiang (2010), agricultural modernisation is divided into four aspects: agricultural production modernisation, agricultural management modernisation, agricultural output modernisation and agricultural sustainable development, on this basis, the depth of agricultural insurance and agricultural carbon emission intensity were increased as two secondary indicators. A total of 16 secondary indicators are defined, as shown in Table 2. According to Wu (2011), this paper employs entropy weight-grey correlation analysis to measure the level of agricultural modernisation. The calculation steps are as follows:

Step1 Calculate the weight of the index; since the calculation steps of the entropy method have already been described in the previous section, there is no need to repeat them in this section.

Step2 Determine the reference sequence and compare the sequence: the reference series consists of the data obtained from the standardized processing of various indicators; The comparison series consists of the optimal values of each indicator.

Step3 Calculate the correlation coefficient: $\varphi_j = \frac{\min|x_{ij} - x_{ij}^*| + \rho \max|x_{ij} - x_{ij}^*|}{|x_{ij} - x_{ij}^*| + \rho \max|x_{ij} - x_{ij}^*|}$

Step4 Calculate the weighted correlation: $r_i = \sum_{j=1}^n W_j \times \varphi_j$, here $\rho = 0.5$

4.2.4. Control variables

To account for other factors that might influence the empirical results, this paper selected four control variables with appropriate measurements to examine their impact on the structural relationships between the constructs:

- **Tra**: the level of transportation facilities, measured as the number of highway mileage/area of the administrative district. Xiong et al.

Table 1
Digital economy indicator system.

Level 1 indicators	Secondary indicators	Interpretation of indicators	Indicator properties
Digital infrastructure	Level of Internet broadband facilities	Internet broadband access port	+
	Long-haul cable density	Length of long-distance fiber-optic cable lines/area of administrative district	+
	Level of communications facilities	Number of cell phone base stations	+
Digital industrialization	Level of development of the telecommunications industry	Total telecommunication services/total population	+
	Level of development of the postal sector	Total postal operations/total population	+
	Level of development of the software industry	Software business revenue/regional GDP	+
Industrial digitization	Level of e-commerce development	E-commerce sales	+
	Enterprise informatization level	Websites per 100 businesses	+
	Level of digital financial inclusion	Digital Inclusive Finance Index	+
Digital popularity	Internet penetration	Internet broadband access users/total population	+
	Digital TV penetration	Number of digital television subscribers/total population	+
	Cell phone penetration rate	Cell phone subscribers per 100 population	+

(2022) pointed out that transport infrastructure can reduce the loss of agricultural products in transport and storage, improve the profitability of agricultural products, increase the income of farmers, and provide a convenient environment for the modernisation of agriculture;

- **Hum**: the level of human capital, measured as the logarithmic number of students enrolled in tertiary education per 100,000 population. Shen et al. (2014) noted that agricultural labour who receive more education are able to acquire more knowledge about facility-based agriculture and agricultural technology, which promotes agricultural modernisation;
- **Gov**: the degree of financial support for agriculture, referring to the study of Yang and Li (2013), the degree of fiscal support for agriculture is measured by local fiscal expenditure/local fiscal expenditure on agriculture, forestry and water;
- **Str**: the proportion of the area planted with food crops to total sown crop area. This study depicts the planting structure of farmers from the perspective of food crops.

4.2.5. Intermediate variables

In this paper, technological innovation (Tec) is used as a mediating variable, and based on the availability of data and drawing on the study of Lin and Xiao (2022) and Qian et al. (2020), the level of regional technological innovation is reflected by the number of domestic patent applications received, and the proportion of the number each province obtained to the national total is adopted for measurement.

4.3. Model selection

To select the optimal model suitable for the panel data in this paper, we conducted F test, LM test and Hausman test. The test results are shown in Table 3. Among them, the p-value of the F-test statistic is 0.0000, which strongly rejects the null hypothesis and considers the fixed-effect model superior to the mixed-effect model. The P-value of the LM test statistic is 0.0000, meaning that the null hypothesis is also rejected, and it is considered that the random effects model is superior to the mixed effects model. Next, an optimal choice needs to be made between the fixed-effects model and the random-effects model. The results show that the p-value of the Hausman test statistic is less than 0.05. Therefore, the null hypothesis is rejected, and it is considered that the fixed-effects model is superior to the random-effects model. To sum up, through the above tests, the fixed effects model is selected for this research.

Therefore, in this paper, the fixed effects model (1) is constructed for the benchmark regression analysis.

5. Empirical results and analysis

5.1. Descriptive statistics

The results of the descriptive statistics of the variables in this paper are shown in Table 4. The mean value of the core explanatory variables of the digital economy ranges from 0.191, with a minimum of 0.041 and a maximum of 0.565, indicating a significant disparity in the level of digital economy development across different regions in China. For the explanatory variables related to agriculture modernisation, the minimum value is 0.366, and the maximum value is 0.754, suggesting a smaller regional gap. The standard deviation of 0.051 for agricultural modernisation is smaller than that of the digital economy, indicating that the digital economy exhibits greater variation across regions compared to agricultural modernisation.

5.2. Benchmark regression analysis

Based on the results of Hausman test, this research uses “province-year” fixed effect models to examine the direct impact of digital economy on agricultural modernisation, and the results are presented in Table 5. This progressive regression method was employed, and the regression results show that as control variables were added gradually, the estimated coefficients of the explanatory variables digital economy in columns (1) to (5) are all positive, which indicates that the digital economy has a positive driving effect on agriculture modernisation. With the increased level of digital economy development, agriculture modernisation will also be increased to a certain extent; and the estimated coefficients are all significant at the level of 1%, indicating that the regression results are highly robust. In addition, comparing the regression coefficients of the digital economy in columns (1) and (2) to (5), the estimated coefficient of the digital economy is 0.234 without control variables. When control variables are gradually added, the coefficient decreases to 0.1555, indicating the omitting controls would overstate its positive effect on agricultural modernisation. After adding control variables, the R^2 value increases from 0.884 to 0.896, indicating that the addition of control variables improves the fit of the model. The above results show that the digital economy has a significant positive driving effect on agricultural modernisation, which is consistent with the analysis of the previous mechanism, thus the research hypothesis 1 is supported.

5.3. Mechanism tests

Table 6 presents the results of analyzing the mediating effects of technological innovation in the relationship between the digital economy driving agricultural modernisation. Column (6) shows the impact of

Table 2
Indicator system for agricultural modernisation.

Level 1 indicators	Secondary indicators	Interpretation of indicators	Indicator properties ^a
Modernisation of agricultural production	Level of agricultural mechanization	Agricultural machinery power/cultivated land area	+
	Level of farmland hydration	Effective irrigated area/total sown area of crops	+
	Rate of agricultural film utilization	Agricultural film use/area sown to crops	+
	Water consumption in agriculture, 10,000 tons	Agricultural water use/gross agricultural output	-
Modernisation of agricultural operations	Share of expenditure on agriculture, forestry and water affairs	Expenditure on agriculture, forestry and water affairs/gross output value of agriculture, forestry, animal husbandry and fisheries	+
	Level of development of agricultural production services	Output of agriculture, forestry and fishery services/total output of agriculture, forestry and fishery services	+
	Level of diversification in the plantation industry	Non-food planted area/crop sown area	+
	Depth of agricultural insurance	Agricultural insurance premium income/gross agricultural output	+
Modernisation of agricultural output	Level of farmers' income	Per capita disposable income of farmers	+
	Food output rate	Total food production/area under food cultivation	+
	Labor productivity	Gross output value of agriculture, forestry, livestock and fisheries/population employed in the primary sector	+
	Land productivity	Gross agricultural output/area sown under crops	+
Sustainable agricultural development	Intensity of pesticide use	Pesticide use/total sown area of crops	-
	Fertilizer application intensity	Fertilizer use/total sown area of crops	-
	Carbon intensity of agriculture	Total agricultural carbon emissions/total agricultural output	-
	forest cover	Forest area/land area	+
	Agricultural disaster rate	Area affected/area affected	-

^a Indicator properties: refer to the role that this indicator plays in the aggregate, both positively and negatively.

Table 3
Panel data model selection test results.

Test type	Statistic	p-value	Test result
F test	29.76	0.0000	The fixed-effects model is superior to the mixed-effects model
LM test	592.99	0.0000	The random effects model is superior to the mixed effects model
Hausman test	13.36	0.0203	The fixed effects model is superior to the random effects model

Table 4
Descriptive statistics of variables.

VarName	Obs	Mean	Median	SD	Min	Max
Agr	300	0.407	0.392	0.051	0.366	0.754
Dig	300	0.191	0.165	0.109	0.041	0.565
Tec	300	11.104	11.220	1.276	7.336	13.809
Tra	300	1.001	0.967	0.523	0.101	2.276
Gov	300	0.114	0.114	0.036	0.039	0.204
Hum	300	7.956	7.951	0.283	7.107	8.672
Str	300	0.647	0.633	0.150	0.355	0.971

Table 5
Benchmark regression results.

Variables	(1)	(2)	(3)	(4)	(5)
	Agr	Agr	Agr	Agr	Agr
Dig	0.234*** (4.270)	0.229*** (4.321)	0.231*** (4.299)	0.207*** (4.510)	0.155*** (4.168)
Tra		-0.016 (-1.571)	-0.016 (-1.573)	-0.012 (-1.260)	-0.023** (-2.079)
Gov			-0.076 (-0.984)	-0.025 (-0.360)	-0.068 (-0.899)
Hum				-0.044** (-2.295)	-0.052*** (-2.662)
Str					-0.230*** (-3.206)
_cons	0.363*** (33.259)	0.379*** (36.199)	0.388*** (32.008)	0.736*** (4.807)	0.968*** (5.082)
Obs	300	300	300	300	300
Groups	30	30	30	30	30
R ²	0.884	0.884	0.884	0.886	0.896

Note: ① t-values are in parentheses. ② *, **, and *** indicate significant at 10%, 5%, and 1% significance levels, respectively.

Table 6
Results of the analysis of indirect effects.

Variables	(6)	(7)
	Agr	Tec
Dig	0.155*** (4.168)	0.050* (1.960)
Tra	-0.023** (-2.079)	0.002 (0.333)
Gov	-0.068 (-0.899)	0.030 (0.534)
Hum	-0.052*** (-2.662)	0.015** (2.454)
Str	-0.230*** (-3.206)	0.006 (0.372)
_cons	0.968*** (5.082)	-0.103** (-2.085)
Obs	300	300
Groups	30	30
R ²	0.896	0.973

Note: ① t-values are in parentheses. ② *, **, and *** indicate significant at 10%, 5%, and 1% significance levels, respectively.

the digital economy on agricultural modernisation; column (7) reports the effect of technological innovation on digital economy. The coefficient estimate of digital economy in column (7) is significant at the 10% level, indicating that the development of digital economy can significantly improve technological innovation. First, the development of the digital economy will continuously increase the demand for digital technology, forcing the improvement of the level of technological innovation; second, along with the development of the digital economy, the state will also increase the investment in talents and funds for technological innovation, so as to make it meet the new needs of the ever-developing digital economy; third, the development of the digital

economy means that the digital infrastructure is constantly improving, and the digital industrialization and industrial digitization are constantly deepening, which provides the superior development environment for the improvement of technological innovation level. Furthermore, technological innovation measured by patents can promote the process of agricultural modernisation. These results are consistent with the previous mechanism analysis, so the research hypothesis 2 is supported.

5.4. Endogeneity test

If there is a reverse causality between the explanatory variables and the explained variables, the endogeneity problem arises, so this section introduces two methods instrumental variables and uses the two-stage least squares (2sls) method to conduct the endogeneity test. The 1st instrumental variable chosen is the lagged one period (L_Dig) of the digital economy, the core explanatory variable of this paper, as an instrumental variable with reference to Yi and Zhou (2018), and the regression results are shown in Table 7. Column (8) reports the results of the first step of the regression: the coefficient estimate of the instrumental variable on the core explanatory variable is positive and significant at the 1% level, indicating that the lagged one period of the digital economy, i.e., L_Dig, is strongly correlated with the digital economy, and it is appropriate to use it as an instrumental variable. Column (9) reports the results from the second step of the regression: the coefficient estimate of the core explanatory variable, digital economy, is positive and passes the significance test at the 1% level. These result reveal that there is a significant positive driving effect of digital economy on agricultural modernisation. In addition, The results of the Wald test and the LM test show that there is no problem of unidentifiable and weak instrumental variables for this instrumental variable.

The 2nd method is to construct the interaction term (Pos_Int) between the number of post offices per million people in each region in 1984 and the number of Internet users in the country in the previous year as an instrumental variable for digital economy, drawing on Nunn and Qian (2014), Huang et al. (2019) and Zhao et al. (2020). The results are shown in columns (10) and (11) of Table 7. The coefficient estimate

Table 7
Endogeneity test results.

Variables	2sls (L_Dig)		2sls (Pos_Int)	
	(8)	(9)	(10)	(11)
	2sls_1	2sls_2	2sls_1	2sls_2
	Dig	Agr	Dig	Agr
L_Dig	0.743*** (8.634)			
Pos_Int			−0.001*** (−6.185)	
Dig		0.132*** (3.505)		0.606*** (5.556)
Controls	containment	containment	containment	containment
non- identifiability test (Kleibergen- Paap rk LM)	p-value: 0.000		p-value: 0.003	
weak instrumental variables test (Kleibergen- Paap rk Wald F)	F-statistic threshold value	74.55 16.38	F-statistic threshold value	38.25 16.38
Obs	270		300	
Groups	30		30	
R ²	0.929		0.548	

Note: ① t-values are in parentheses. ②*, **, and *** indicate significant at 10%, 5%, and 1% significance levels, respectively.

for digital economy is positive and significant at the 1% level, indicating that the effect of digital economy driving agricultural modernisation holds. In addition the validity results of the instrumental variable indicate that the instrumental variable does not suffer from the problem of unidentifiable and weak instrumental variables. All the above test results are consistent with the findings from the baseline regression model, showing that digital economy has a significant positive driving effect on agricultural modernisation.

5.5. Robustness tests

Robustness testing is necessary to test the stability and reliability of the model or method used under different conditions. The following three methods were adopted to test the robustness of the model and results are presented in Table 8:

- (1) Excluding municipalities directly under the central government. Given the significant differences in digital economy development levels between China's four municipalities directly under the central government and other provinces and cities, these four municipalities are excluded from the robustness test, following the approach used in Zhou et al. (2021). Column (12) in Table 8 reports the regression results after excluding the 4 municipalities. The coefficient estimate of the core explanatory variable digital economy passes the test at the 1% significance level, indicating that the driving effect of digital economy on agricultural modernisation is still significant, a result that is closer to that of the above model, suggesting that the above model is robust.
- (2) Shortening the sample period. This paper uses the panel data of 30 provinces and cities in China from 2014 to 2023, and in order to verify the robustness of the model, the sample period is shortened and the panel data of 30 provinces and cities from 2014 to 2021 are selected for the regression. The regression results after shortening the sample period are reported in Column (13). The coefficient estimate of the core explanatory variable digital economy is significant at the 1% level, indicating that the driving effect of digital economy on agricultural modernisation is still significant, and the above model is considered robust.
- (3) Replacement of explanatory variables. The principal component analysis was adopted to re-measure the level of digital economy development in 30 provinces and cities, and three principal components are extracted based on the eigenvalues of the variables, and the level of digital economy development in each province and city is re-measured based on the contribution rate of each principal component. The regression results of the model

Table 8
Robustness test results.

Variables	(12)	(13)	(14)
	Agr	Agr	Agr
Dig	0.057*** (4.316)	0.146*** (3.023)	0.108*** (4.894)
Tra	0.019** (2.400)	−0.027** (−1.973)	0.002 (0.320)
Gov	−0.090*** (−2.922)	−0.090 (−0.939)	−0.030 (−0.297)
Hum	−0.013* (−1.818)	−0.083*** (−3.268)	0.071*** (7.510)
Str	−0.074*** (−3.791)	−0.273*** (−3.380)	−0.144*** (−9.405)
_cons	0.535*** (8.791)	1.250*** (4.946)	−0.084 (−1.110)
Obs	260	240	300
Groups	26	30	30
R ²	0.926	0.871	0.479

Note: ① t-values are in parentheses. ②*, **, and *** indicate significant at 10%, 5%, and 1% significance levels, respectively.

after replacing the explanatory variables are reported in Column (14), and the coefficient estimate of digital economy is positive and passes the significance test at the 1% level, which proves that the above model is robust.

6. Further analysis

6.1. Heterogeneity analysis

6.1.1. Analysis of regional heterogeneity

According to the results of the previous analysis, it can be seen that the digital economy at the national level has a significant positive driving effect on agricultural modernisation, but considering the vast territory of China, there are large differences in the level of development of the digital economy in various regions, so this subsection carries out a regional heterogeneity analysis. China is divided into three regions of east, middle and west,¹ to examine whether the positive impact of digital economy on agricultural modernisation varies across these regions, and the regression results are shown in Table 9.

Following the same regression analysis as discussed in Section 5.2, the impacts of digital economy on agricultural modernisation are obtained for the eastern, central and western regions of China, respectively, as reported in Columns (15)–(17) in Table 9. The estimated coefficients of the explanatory variable digital economy is positively significant at the 1% level in the western regions, but insignificant in the eastern regions and central regions. Several factors may contribute to this finding: first, in eastern region, most provinces and cities started developing digital economy early, resulting in well-established digital infrastructure. Agriculture has long benefited from these developments, and the level of agricultural modernisation in the eastern region is relatively high. Consequently, the marginal benefits of further digital driven modernisation of agriculture are limited. Second, in the central region, agriculture is relatively advanced, characterized by large-scale

Table 9
Results of regional heterogeneity analysis.

Variables	(15)	(16)	(17)
	Eastern regions	Central regions	Western regions
	Agr	Agr	Agr
Dig	0.064 (1.281)	0.027 (0.804)	0.086*** (3.669)
Tra	−0.036 (−1.244)	0.010 (1.459)	−0.004 (−1.176)
Gov	0.724** (2.593)	0.047 (1.070)	−0.094* (−1.703)
Hum	−0.117*** (−2.682)	0.023** (2.107)	−0.006 (−0.740)
Str	−0.351*** (−3.406)	−0.097*** (−3.376)	−0.061* (−1.889)
_cons	1.556*** (4.122)	0.260*** (2.856)	0.470*** (7.220)
Obs	120	90	90
Groups	12	9	9
R ²	0.895	0.949	0.815

Note: ① t-values are in parentheses. ② *, **, and *** indicate significant at 10%, 5%, and 1% significance levels, respectively.

¹ The eastern region includes: 12 provinces and municipalities: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, Hainan; the central region includes: 9 provinces and municipalities: Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan; and the western region includes: 9 provinces and municipalities: Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang.

operations and a complete industrial chain. Here, the digital economy primarily plays an “optimization” role, with limited short term impact on macro indicators. Lastly, in the western region, where the starting point of agricultural modernisation is lower than the eastern and central regions, the digital economy has greater potential for marginal improvements and can drive substantial progress.

6.1.2. Analysis of heterogeneity in food production layout

Heterogeneity analysis of grain production layout was carried out using the approach outlined in Li and Ruan (2023). In 2003, China divided 31 provinces into three categories: main grain producing areas, main grain marketing areas, and areas with a balance of production and marketing.² Columns (18) to (20) in Table 10 report the results of the heterogeneity analysis for each of these categories. The estimated coefficients of the digital economy in both grain-producing regions and production–marketing balance areas are positive and significant at the 1% level. Notably, the coefficients for balance areas exceed those for grain-producing regions, which is broadly consistent with the regional heterogeneity analysis above. Grain-producing regions are primarily located in central China, grain-marketing regions in the east, and balance areas largely in the west. In grain-producing regions, digital technologies enhance the efficiency of large-scale farming, though their marginal effects are constrained by entrenched production systems. By contrast, the stronger effects in balance areas can be attributed to their diversified agricultural structures, where tools such as e-commerce platforms and digital traceability systems unlock greater value-added potential, supported by lower baseline modernisation levels and targeted policy measures. In grain-marketing regions, however, the effect is statistically insignificant, likely due to resource diversion associated with urbanization and diminishing returns in already advanced agricultural systems.

Table 10
Results of the heterogeneity analysis of the layout of food production.

Variables	(18)	(19)	(20)
	The main grain-producing areas	The main grain-selling areas	The balance of production and marketing areas
	Agr	Agr	Agr
Dig	0.075*** (2.817)	−0.097 (−1.006)	0.085*** (3.641)
Tra	−0.002 (−0.391)	−0.136*** (−2.709)	−0.003 (−0.818)
Gov	0.047 (1.204)	1.677*** (3.498)	−0.065 (−1.408)
Hum	0.015* (1.728)	−0.130* (−1.691)	−0.003 (−0.446)
Str	−0.066** (−2.301)	−0.664*** (−3.996)	−0.071** (−2.515)
_cons	0.306*** (4.288)	1.953*** (2.921)	0.450*** (8.270)
Obs	130	70	100
Groups	13	7	10
R ²	0.919	0.888	0.873

Note: ① t-values are in parentheses. ② *, **, and *** indicate significant at 10%, 5%, and 1% significance levels, respectively.

² The main grain-producing areas include: Liaoning, Hebei, Shandong, Jilin, Inner Mongolia, Jiangxi, Hunan, Sichuan, Henan, Hubei, Jiangsu, Anhui, Heilongjiang, 13 provinces and cities; the main grain-selling areas include: Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong, Hainan, 7 provinces and cities; the balance of production and marketing areas include: Shanxi, Ningxia, Qinghai, Gansu, Yunnan, Guizhou, Chongqing, Guangxi, Shaanxi, Xinjiang, 10 provinces and cities.

6.2. Analysis of spatial spillover effects

6.2.1. Spatial auto-correlation test

This paper uses global spatial auto-correlation test to examine the agricultural modernisation level of 30 provincial administrative regions in China during the observation period. Global spatial auto-correlation test for agricultural modernisation using Moran's I (Moran's I), calculated as:

$$\text{Moran's } I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (3)$$

Where n denotes the number of provinces and municipalities; w_{ij} is the spatial weight matrix; S^2 denotes the sample variance; and $\bar{x}$ denotes the mean of n x_i . Based on the geo-economic matrix, all Moran's I indices passed the significance test of 1% from 2014 to 2023 (shown in Table 11), which indicates that there is spatial correlation and significant spatial agglomeration effect in China's agricultural modernisation. Therefore, it is necessary to incorporate the spatial dimension into the construction framework of the basic econometric model and conduct quantitative assessment of the influencing factors of agricultural modernisation in China based on the spatial econometric analysis paradigm.

6.2.2. Selection of a spatial measurement model

To rationally select the form of spatial econometric models and ensure the validity of the estimation results, this paper conducts a series of normative tests, including LM test, Robust LM test, LR test, Wald test and Hausman test, to determine whether spatial effects need to be introduced and the specific type of model setting.

The test results of LM-Lag and LM-Error are shown in Table 12. The results show that the LM statistics of both types of tests are significant at the 1% significance level, indicating that the explained variable may not only be affected by its own spatial proximity values but also by the spatial diffusion of the error term. This result rejects the assumptions set by the traditional OLS model, indicating that spatial correlation cannot be ignored in the model and providing statistical support for the introduction of spatial econometric models.

Furthermore, to determine which form of spatial model is more reasonable, this paper made a model selection among the spatial lag model (SAR), spatial error model (SEM), and spatial Durbin model (SDM), and the results are shown in Table 13. The results show that the LR test and Wald test statistics of the spatial Durbin model are both significant at the 1% significance level, indicating that SDM cannot be simplified to SAR or SEM, that is, the explained variable is not only affected by its own spatial proximity values, but also by the spatial proximity values of the explanatory variables simultaneously. The spatial Durbin model more comprehensively characterizes the spatial overflow mechanism and is therefore suitable for the analysis in this paper.

Table 11
Global moran index I.

Particular year	Moran's I	z	p-value
2014	0.278	3.3	0.000
2015	0.304	3.68	0.000
2016	0.344	4.364	0.000
2017	0.351	4.655	0.000
2018	0.287	4.233	0.000
2019	0.283	4.498	0.000
2020	0.307	4.25	0.000
2021	0.335	4.332	0.000
2022	0.344	4.261	0.000
2023	0.324	4.118	0.000

Table 12
Results of LM test.

Type of test	Test results	p-value
LM_spatial_erro	37.225	0.000
Robust LM_spatial_erro	26.077	0.000
LM_spatial_lag	15.771	0.000
Robust LM_spatial_lag	4.623	0.032

Table 13
Results of LR test.

Type of test	Model Selection	Test results	p-value
LR test	LR test SDM SAR	39.18	0.0000
	LR test SDM SEM	42.53	0.0000
Wald test	Wald Test for SAR	39.44	0.0000
	Wald Test for SEM	35.22	0.0000

The next step is to choose between the random effects and fixed effects models and conduct the Hausman test for this. The p-value of the Hausman test results was significant at the 1% level, leading to the selection of the fixed-effects model. To further select the individual fixed effects model, the time fixed effects model and the bidirectional fixed effects model, we conducted the LR test, and all results passed the significance test. This indicates that time fixed effect, individual fixed effect and bidirectional fixed effect models can be selected. The time-fixed model accurately identifies the spatial overflow mechanism while avoiding the multicollinearity of the spatial lag term (Wx) and individual fixed effects, and simultaneously controls the common time-varying shock of the entire sample to ensure the unbiased and validity of the estimation results. Therefore, this paper selects the time-fixed Effects SDM model for analysis. The specific results are shown in Table 14.

The SDM constructed in this paper takes the following form:

$$Y_{it} = \alpha + \rho \sum_{j=1}^n w_{ij} Y_{jt} + \beta X_{it} + \delta \sum_{j=1}^n w_{ij} X_{jt} + \lambda \text{Controls}_{it} + \sigma \sum_{j=1}^n w_{ij} \text{Controls}_{jt} + \eta_i + \varepsilon_{it} \quad (4)$$

Where ρ is the spatial correlation coefficient; w_{ij} is the spatial weight matrix; δ is the marginal impact of the digital economy of neighboring regions on the modernisation of agriculture in the region; η_i is the time fixed effects; ε_{it} is the spatial error term.

6.2.3. Regression results of spatial Durbin model

To systematically examine the impact of the digital economy on agricultural modernisation, this paper uses the estimation results of the spatial Durbin model, and the results are shown in Table 15. The results show that the spatial auto-regressive coefficient ρ is significantly positive, indicating that agricultural modernisation has obvious spatial dependence in space and presents distinct spatial agglomeration characteristics. The coefficient of the digital economy is 0.2930, which is significant at the 1% significance level. Furthermore, the spatial lag term coefficient of the digital economy is 0.3092, which is significant at the 10% significance level, indicating that the increase of the digital economy in neighboring regions has significantly enhanced the local agricultural modernisation level through spatial spillover effects. Thus, **hypothesis 3** is supported.

Table 14
Hausman test.

Type of test	Test results	p-value
Hausman test	72.41	0.0000
LR test	LR test both individual	51.82
	LR test both time fixed	429.98

Table 15
SDM regression results based on the geo-economic matrix.

Variables	Main	Wx	LR_Direct	LR_Indirect	LR_Total
Dig	0.2930*** (4.46)	0.3092* (1.93)	0.3321*** (4.84)	0.7053*** (3.01)	1.0375*** (3.83)
Controls	containment				
Spatial	Rho	0.4110*** (4.82)			
Variance	sigma2_e	0.0023*** (11.99)			
Obs	300				
Groups	30				
R ²	0.4098				

Note: ① t-values are in parentheses. ② *, **, and *** indicate significant at 10%, 5%, and 1% significance levels, respectively.

Further decomposition of the impact effect of the digital economy can be found that the direct effect, indirect effect and total effect of the digital economy are all positive and have passed the significance test at the 1% level, indicating that the development of the digital economy has a significant positive driving effect on the region and neighboring regions. Further observation of the size of the estimated coefficients can be found, the indirect effect of the digital economy is greater than the direct effect, indicating that the development of the digital economy on the neighboring regions of the positive driving effect is stronger, the development of the digital economy in a region can not only promote the level of modernisation of agriculture in the region to improve the level of modernisation of agriculture in the region, but also to drive the development of modernisation of agriculture in neighboring regions. Therefore, we should not only focus on the development of the digital economy in the region, but also pay more attention to the synergistic development of neighboring regions, so as to better exert the spatial spillover effect of the digital economy and promote the process of agricultural modernisation.

7. Conclusions and future work

This study set out to examine how the digital economy contributes to agricultural modernisation in China, with particular attention to mechanisms, spatial spillovers, and regional differentiation. Drawing on provincial panel data and spatial econometric analysis, the findings provide robust evidence that the digital economy is an important driver of agricultural modernisation, advancing productivity, resilience, yields, and product quality. These effects extend beyond individual regions, as digital economy development generates significant spatial spillovers that promote agricultural modernisation in neighboring areas.

The analysis further demonstrates that technological innovation plays a key mediating role in this process. Digitalisation enhances innovation capacity, which in turn improves production efficiency, strengthens resilience to natural and climatic risks, and supports quality upgrading in agriculture. This finding reinforces the argument that the role of the digital economy in agriculture extends beyond direct productivity gains and instead operates through broader structural and technological transformation processes. Such mechanisms align with earlier conceptual discussions on digital agriculture and innovation systems (Basso and Antle, 2020), while providing empirical evidence on how digitalisation translates into tangible modernisation outcomes.

At the same time, the results reveal substantial regional heterogeneity. The effects of the digital economy are strongest in western regions and in major grain-producing and production–marketing balance areas, while impacts are weaker or insignificant in more developed eastern and central regions. This pattern suggests diminishing marginal returns in already modernised agricultural systems, where digital infrastructure

and technological capabilities are relatively mature. The finding is consistent with broader debates in rural and regional development literature that emphasises the uneven spatial distribution of digital transformation and innovation benefits (Granado-Díaz et al., 2024; McCampbell et al., 2022). It also highlights the risk that digitalisation may reinforce existing regional disparities if complementary resources such as human capital, infrastructure, and institutional capacity are unevenly distributed.

In summary, these findings contribute to the reviewed frameworks and rural studies literature in three key ways. First, extending the conceptual insights of Bridgman et al. (2024) and addressing the research gap identified by Wang et al. (2025) and Liu and Lin (2025), this study demonstrates that digital economy-driven agricultural modernisation is spatially uneven, moving beyond national average effects to reveal different regional dynamics. Second, the study provides empirical evidence on the mechanisms linking digitalisation and agricultural modernisation, complementing earlier work that emphasized the transformative potential of digital technologies in agriculture but offered limited empirical analysis of the pathways (Leng, 2022; Basso and Antle, 2020). Third, by identifying spatial spillover effects, this research responds to calls in recent rural transformation studies (Granado-Díaz et al., 2024; McCampbell et al., 2022) to understand agricultural modernisation not only as a localised process but also as one embedded in inter-regional networks of digital infrastructure, knowledge flows and innovation diffusion.

From a policy perspective, the results suggest that strategies for digitally enabled agricultural modernisation should be spatially differentiated. Investments in digital infrastructure, innovation capacity, and human capital are likely to yield the greatest returns in less-developed and agriculturally significant regions, while coordinated regional approaches are needed to harness positive spillovers and avoid widening rural inequalities. At the same time, attention should be paid to digital skills, affordability, and institutional support to ensure that digitalisation contributes to inclusive rural development rather than reinforcing existing divides.

This study has limitations. Both the digital economy and agricultural modernisation are complex and evolving concepts, and indicator construction remains constrained by data availability and measurement choices. Future research could extend this analysis by incorporating micro-level data, examining household and community-level livelihood outcomes, and exploring longer-term social and environmental consequences of digitalisation in rural areas. Such work would further enrich understanding of how digital transformations are reshaping rural economies and societies.

CRediT authorship contribution statement

Pan Hong: Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Tan Shuang:** Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing. **Liu Mingyu:** Methodology, Software, Validation, Visualization, Writing – review & editing. **Ying Xie:** Formal analysis, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing. **Suwan (Cheng) Long:** Investigation, Validation, Visualization, Writing – review & editing.

Declaration of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Appendix

Entropy weights-TOPSIS method steps.

Step 1 Data standardization:

If the index is positive, $x_{ij}^* = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$, If the index is negative, $x_{ij}^* = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)}$, here x_{ij} denotes the raw value of indicator j for area i .

Step 2 Calculate the weight of the value:

$$p_{ij} = \frac{x_{ij}^*}{\sum_{i=1}^m x_{ij}^*}$$

Step 3 Calculate the entropy of the index:

$$e_j = -k \sum_{i=1}^m p_{ij} \ln(p_{ij}), \text{ here } k = \frac{1}{\ln(m)}$$

Step 4 Calculate the information utility value:

$$d_j = 1 - e_j$$

Step 5 Calculate the weight of the index:

$$W_j = \frac{d_j}{\sum_{j=1}^n d_j}$$

Step 6 Construct a weighted matrix:

$$z_{ij} = x_{ij}^* \times W_j$$

Step 7 Calculate positive and negative ideal solutions

Positive ideal solution:

$$z_{ij}^+ = \begin{cases} \max(z_{ij}), j \text{ is a positive index} \\ \min(z_{ij}), j \text{ is a negative index} \end{cases}$$

Negative ideal solution:

$$z_{ij}^- = \begin{cases} \min(z_{ij}), j \text{ is a positive index} \\ \max(z_{ij}), j \text{ is a negative index} \end{cases}$$

Step 8 Calculate the optimal and inferior distances

The optimal distance:

$$D_i^+ = \sqrt{\sum_{j=1}^n (z_{ij} - z_{ij}^+)^2}$$

The inferior distance:

$$D_i^- = \sqrt{\sum_{j=1}^n (z_{ij} - z_{ij}^-)^2}$$

Step 9 Calculate the closeness of the evaluation index to the optimal scheme:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

Data availability

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