frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 13 April 2023
DOI 10.3389/fenvs.2023.1117086

OPEN ACCESS

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RECEIVED 06 December 2022
ACCEPTED 04 April 2023
PUBLISHED 13 April 2023

CITATION
Xu Y, Li C, Wang X and Wang J (2023), Digitalization, resource misallocation and low-carbon agricultural production: evidence from China.
Front. Environ. Sci. 11:1117086.
doi: 10.3389/fenvs.2023.1117086

Digitalization, resource misallocation and low-carbon agricultural production: evidence from China

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With the rapid development of digital technologies such as artificial intelligence, big data and cloud computing, China's agricultural production is entering a new era characterized by digitalization. Based on provincial panel data of China from 2013 to 2020, this paper adopts the system GMM and mediating effects model to systematically examine the impact of digitalization on low-carbon agricultural production from the perspective of resource misallocation. The results indicate that digitalization can significantly curb agricultural carbon emissions and thus promote low-carbon agricultural production, and this finding still holds after the robustness test. The heterogeneity analysis indicates that the inhibiting effect of digitalization on agricultural carbon emissions is most pronounced in the eastern region relative to the central and western regions (the regression coefficients are −0.400 and −0.126 respectively). Further mechanism analysis suggests that digitalization can reduce agricultural carbon emissions by correcting the widespread capital and labor misallocation in agricultural factor markets. The findings of this study provide significant policy implications for low-carbon agricultural production in China.

KEYWORDS

digitalization, low-carbon agricultural production, agricultural capital misallocation, agricultural labor misallocation, resource misallocation

1 Introduction

Since the industrial revolution, global warming has become increasingly serious due to the continued emissions of greenhouse gases like carbon dioxide (Bekun et al., 2019), resulting in a series of extreme phenomena such as sea-level rise, drought and waterlogging disasters (Mukul et al., 2019). Confronted with the severe situation of global warming, Chinese government promised to peak carbon dioxide emissions by 2030 and strive to achieve carbon neutralization by 2060 (the dual-carbon target) (Wang et al., 2021). Guided by the dual carbon target, the latest Central Document No 1, issued by the Ministry of Agriculture and Rural Affairs of the People's Republic of China in 2022, has emphasized that continuing to promote green development in agriculture and rural areas is an important task in comprehensively promoting rural revitalization (Wen et al., 2022). However, in deep contrast with the proliferation of policies, China's carbon emission from the agricultural sector keeps on growing rapidly from 99 Mt in 1998 to 242 Mt in 2015, which is estimated with an increase of 142% (Chen et al., 2020). In this case, it is urgent for us to explore how to give impetus to low-carbon agricultural production, reduce agricultural carbon emissions and contribute to achieving the dual carbon goal.

Under the new round of technology revolution marked by digital technology, digitalization, with its high penetration, scale and network effects, plays an important role in reorganizing production factors, reshaping economic structure and changing competitive advantages (Brenner and Hartl, 2021; Zhao et al., 2022). According to the China Academy of Information and Communications Technology, the scale of China's digitalization reached $5.681 billion in 2020. Meanwhile, the scale of agricultural digitalization accounted for 22.5%. The rapid rise of digitalization is not only a direct response to the huge changes in the social internal endowment and external environment, but also provides a valuable opportunity for promoting low-carbon agricultural production in China (Fu and Zhang, 2022). Thus, propelling the low-carbon transformation of agriculture from the digitalization perspective is of great significance in accelerating the process of agricultural modernization and achieving the dual carbon goal.

Aside from digitalization, the impact of resource misallocation on low-carbon agricultural production cannot be ignored. Resource misallocation is relative to efficient resource allocation. In an economy where resources can flow freely to achieve Pareto optimality, there is said to be an efficient resource allocation, and resource misallocation presents a deviation from this ideal state (Berthou et al., 2019). Numerous studies show that resource misallocation could lead to wasted resources and reduced resource utilization, which is detrimental to the low-carbon transition in agriculture (Du et al.; Razzaq et al., 2021). There has been an urban bias in China's macro development policy for a long time. The agricultural sector has been relatively disadvantaged in the national economy and resource allocation, which has affected the flow and rational allocation of labor, capital and other important retention (Meng and Zhao, 2018). Therefore, confronted with the rigorous situation of agricultural resource misallocation, it is necessary for us not only to recognize the direct impact of digitalization on low-carbon agricultural production but also to investigate how to make full use of digitalization to achieve efficient resource allocation and reduce agricultural carbon emissions.

This study aims to clarify the relationship between digitalization and low-carbon agricultural production. Compared with the existing literature, the possible marginal contributions of this study are the following three. First, this is the first study to place digitalization, resource misallocation and low-carbon agricultural production into the same analytical framework, which expands and enriches the existing research perspective. Second, the asymmetric relationship between digitalization and low-carbon agricultural production is further analyzed according to the level of economic development in different regions, which makes the demonstration of this paper more stereoscopic and comprehensive. Third, this paper constructs a mathematical model to accurately calculate the degree of agricultural resource misallocation. Then, an empirical examination of the transmission mechanism of digitalization affecting low-carbon agricultural production from the perspective of agricultural capital mismatch and labor mismatch is conducted, which provides empirical evidence to promote low-carbon transition in agriculture for China.

The remainder of this paper is structured as follows: Section 2 summarizes the existing literature. Section 3 examines the theoretical analysis and hypothesis. Section 4 describes the data and methods. Section 5 discusses the empirical results. Section 6 summarizes the conclusions and policy implications.

2 Literature review

2.1 Digitalization and low-carbon agricultural production

The existing studies on the relationship between digitalization and low-carbon agricultural production can be broadly divided into macro and micro levels. From the macro perspective, most scholars believe that digitalization can effectively curb agricultural carbon emissions and promote low-carbon agricultural production (Kamilaris et al., 2017; Zhu and Li, 2021). Balogun et al. (2022) examined the implementation of digitalization in African urban farming by assessing various case studies. They found that introducing digitalization to agriculture can reduce carbon emissions while supporting food availability for the growing number of urban residents. Xu et al. (2022) then explored the impact of digital transformation on agricultural carbon productivity. The empirical evidence indicated that digitalization positively contributes to promoting low-carbon agricultural production. From a micro perspective, Zhou et al. (2022) pointed out that the internet substantially promotes farmers' low-carbon tillage technology adoption and low-carbon fertilization technology adoption after surveying 1080 farmers in Sichuan Province in China. Meanwhile, Huang et al. (2022) further found that digital technology applications can indirectly promote the adoption of low-carbon technologies by influencing farmers' risk perceptions in an empirical test using the field survey data of 571 farm households in Jiangsu Province, China.

2.2 Resource misallocation and low-carbon agricultural production

The persistent resource misallocation not only hinders economic development, but also leads to ecological degradation (He and Qi, 2021). Few studies are available to examine the interlinkage between resource misallocation and agricultural carbon emissions but can be broadly categorized as single-factor and multi-factor misallocation. Regarding single-factor misallocation, Zhang and Xu (2017) found that land misallocation can significantly aggravate carbon emissions across the country. Chu et al. (2019) empirically examined the impact of energy misallocation on carbon emission efficiency based on panel data from 30 provinces in China. The results showed that energy misallocation forces production factors to flow to inferior industries with low returns, especially those with high energy consumption, exacerbating the adverse impact on carbon emission efficiency. Regarding the multi-factor misallocation, Hu et al. (2022) tested the effect of resource misallocation on agricultural green total factor productivity (GTFP) based on panel data from 306 cities in China from 1996 to 2007. The research results suggested that the misallocation of land, labor, machinery, and fertilizer directly hinders GTFP. Qin et al. (2022) further pointed out that the inhibitory effect of factor misallocation on GTFP constantly weakens with the optimization and upgrading of the agricultural and industrial structure and the improvement of agricultural science and technology.

2.3 Digitalization and resource misallocation

Digitalization is unanimously recognized for its effectiveness in reducing resource mismatches and improving allocation efficiency (Asongu and Le Roux, 2017). In terms of labor allocation, Martin et al. (2013) stated that digitalization inevitably leads to the rational allocation of regional human resources by accelerating information sharing and facilitating information coordination. Based on the China Family Panel Studies data, Liu Shi-yang (2022) empirically confirmed this view. They found that digitalization could significantly reduce the degree of labor misallocation through the information improvement effect and the thick labor market effect. In terms of capital allocation, Li et al. (2022) presented the hypothesis that digitalization can increase the firms' internal management and communication efficiency, optimize the division of work, and reduce internal capital misallocation. Li and Pang (2023) conducted empirical research with the innovation data of Chinese A-share and noted that digitalization could effectively correct the financial mismatch problem in the traditional financial model. In addition, Jin et al. (2023) adopted capital deviation and labor deviation to measure resource misallocation and further empirically investigated the impact of digitalization on resource misallocation from the multi-factor perspective. The findings of their study further verified the positive effect of digitalization on reducing resource misallocation.

Overall, evidence from existing studies suggests that low-carbon agricultural production could be influenced by resource misallocation to some extent. Hence, resource misallocation is an important issue that should be considered when assessing the impact of digitalization on low-carbon agricultural production. In light of the foregoing, this study tries to empirically examine the relationship between digitalization, resource misallocation and low-carbon agricultural production based on theoretical analysis.

3 Theoretical analysis and hypothesis

3.1 The direct effect of digitalization on low-carbon agricultural production

Digitalization originates from technology and data elements, and is a disruptive technological innovation that stems from the deep penetration of information technology in the social economy. Its vigorous rise can not only bring extensive and profound impact on the social development pattern but also provide an important opportunity for low-carbon agricultural production. First, digitalization derived from information and communication technology has the essential characteristics of information dissemination across time and space, and the comparative advantage of big data creation and sharing. Thus, digitalization can break through the limitations of time and space to widely disseminate the concept of low-carbon agricultural production and promote low-carbon agricultural production technologies. Second, digitalization has revolutionized traditional agricultural production patterns. With the help of digital technologies such as big data and cloud computing, farmers can collect and analyze crop planting experience and market information, calculate the amount of water and fertilizer needed for crop production, and then make scientific planting decisions to reduce agricultural carbon emissions and achieve low-carbon agricultural production. Third, digitalization strengthens the supervision of agricultural high-carbon behavior. Digitalization can promote the spread of the concept of low-carbon agricultural production and innovate and broaden the channels and methods for government to supervise agricultural production. Accurate identification, appropriate rewards and punishments, and timely correction of high-carbon behaviors in the agricultural production process by government departments can effectively reduce agricultural carbon emissions.

Hypothesis 1. Digitalization is beneficial to reduce agricultural carbon emissions and to drive low-carbon agricultural production

3.2 The indirect effect of digitalization on low-carbon agricultural production

The action process of digitalization on agricultural resource allocation can be roughly divided into three stages: penetration, substitution, and synergy. In the penetration stage, affected by the urban-rural dual system, it is difficult for the agricultural resource to achieve a two-way flow between urban and rural areas, which leads to distortions in the agricultural resource allocation. By expanding the economic right and selecting the range of agricultural production entities, digitalization can further promote the flow and accumulation of production factors such as labor force and capital in accordance with the market supply and demand relationship and the functional positioning of urban and rural industries, and realize the two-way flow of urban and rural resource finally. In the substitution stage, digitalization could substitute agricultural labor and capital resources, releasing redundant labor and capital in all segments of agriculture and achieving the optimal allocation of agricultural resources. First, digitalization directly enhances agricultural intelligence and modernization, reduces labor demand, improves labor quality, and releases redundant agricultural labor. Second, digitalization can strengthen farmers' management and control over the processes of arable land, sowing, fertilization, pesticide application, and harvesting, reduces pesticide and fertilizer use, and releases redundant agricultural capital. In the synergy stage, the digital transformation of agriculture and digital industrialization co-evolve to jointly improve the allocation efficiency of factor resources and reduce agricultural resource misallocation. Relying on strong penetration and substitution effects, digitalization can optimize the entire agricultural industry chain, including production, management, storage and transportation, circulation, and market distribution, thereby reshaping the original element allocation structure. Given the above hypothetical mechanism analysis, we construct a mechanism diagram of the role of digitalization in low-carbon agricultural production (see Figure 1).

Hypothesis 2. Digitalization effectively propels low-carbon agricultural production by reducing the degree of agricultural resource misallocation.

4 Methodology and data

4.1 Methodology

4.1.1 Benchmark model

To test the impact of digitalization on low-carbon agricultural production, a dynamic benchmark model is constructed as follows:

$$\begin{aligned} lnLCA_{it} &= \alpha_0 + \alpha_1 lnLCA_{i,t-1} + \alpha_2 lnDIG_{it} + \alpha_3 lnFAS_{it} + \alpha_4 lnURB_{it} \\ &\quad + \alpha_5 lnSTR_{it} + \alpha_6 lnDIA_{it} + \alpha_7 lnADL_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

Among them, i and t denote provinces and years, respectively. α_i is parameter to be estimated for the model. $lnLCA_{it}$ is the explained variable, which denotes the level of low-carbon agricultural production of the i province in the t year. Given the continuity and accumulation of agricultural carbon emissions, this paper adds one-period lagged explained variable $lnLCA_{i,t-1}$ to the right side of Eq. 1. $lnDIG_{it}$ is the core explanatory variable, which denotes the level of digitalization of the i province in the t year. $lnFAS_{it}, lnURB_{it}, lnSTR_{it}, lnDIA_{it}, lnADL_{it}$ are control variables, which denote agricultural fiscal expenditure, urbanization, agricultural structure, natural disasters and the level of agricultural economic development. ε_{it} denotes the stochastic disturbance term.

4.1.2 Mediating effect model

To validate whether digitalization can promote low-carbon agricultural production by reducing agricultural resource misallocation, this paper draws on the research of Baron and Kenny (1986) and MacKinnon et al. (2007) adopts the stepwise regression to test the mediating effect. The stepwise regression covers three steps. In addition to Eq. 1, the following two regressions should be constructed.

$$\begin{aligned} lnM_{it} &= \beta_0 + \beta_1 lnM_{i,t-1} + \beta_2 lnDIG_{it} + \beta_3 lnFAS_{it} + \beta_4 URB_{it} \\ &\quad + \beta_5 STR_{it} + \beta_6 DIA_{it} + \beta_7 ADL_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} lnLCA_{it} &= \delta_0 + \delta_1 lnLCA_{it} + \delta_2 lnDIG_{it} + \delta_3 lnM_{it} + \delta_4 lnFAS_{it} \\ &\quad + \delta_5 lnURB_{it} + \delta_6 lnSTR_{it} + \delta_7 DIA_{it} + \delta_8 ADL_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

First, Eq. 1 is estimated to test whether low-carbon agricultural production is affected by digitalization. Next, all mediating variables, including agricultural capital misallocation and labor misallocation, are regressed against digitalization, as shown in Eq. 2. Finally, low-carbon agricultural production is regressed against both the main variable of digitalization and the mediating variables in Eq. 3. Where lnM_{it} is the mediating variable in Eq. 2, which denotes agricultural capital misallocation ($lnCMI_{it}$) and agricultural labor misallocation ($ln\,LMI_{it}$). Eq. 2 also introduces a lag period of the intermediary variable ($lnM_{i,t-1}$) to reduce the possibility of missing variables and ensure the robustness of the model set. Other variables in Eq. 2 have the same meaning as in Eq. 1. The definition of the variables in Eq. 3 is also the same as in Eq.1–2.

4.2 Variables

4.2.1 Explained variable

The explained variable is low-carbon agricultural production (LCA), which is measured by employing agricultural carbon emissions (ACE). According to Johnson et al. (2007) and Cui et al. (2022), agricultural carbon emissions come mainly from agricultural production activities (chemical fertilizer, agricultural film, pesticide, diesel oil, plowing, agricultural irrigation), rice cultivation (paddy field) and livestock and poultry farming (pigs, cattle, sheep). After determining agricultural carbon source, this paper calculates agricultural carbon emissions according to the following formula:

$$ACE = \sum ACE_i = \sum \delta_i T_i \tag{4}$$

Where ACE denotes agricultural carbon emissions. ACE_i indicates the carbon emissions of each carbon source. T_i is the number of carbon sources. δ_i is the coefficient of carbon emission of each carbon source. The carbon sources and its carbon emissions coefficient are shown in Table 1 for details.

4.2.2 Core explanatory variable

Digitalization (DIG) is the core explanatory variable. Drawing on the research of Yang et al. (2022), 13 indicators are selected from three aspects: digital foundation, digital industrialization, and industrial digitalization to construct a more objective digitalization index system. After constructing the digitalization index system, it is necessary to determine the weights of each index. The entropy method, which can avoid the error caused by subjective judgment, is chosen to measure the weights of each index in this paper (Yi et al., 2022). The specific indicators and their weights can be seen in Table 2.

As shown in Table 2, the weights of digital foundation, digital industrialization and industrial digitalization are 0.407, 0.264 and 0.328, respectively. Specifically, in digital foundation, the weight of the number of web pages is larger, which is an important factor affecting the digital foundation. In digital industrialization, the weight of software business income is 0.132, significantly higher than other indicators, indicating that software business income is an essential indicator reflecting digital industrialization. In industrial digitalization, E-commerce sales have the largest weight of 0.098, which reveals the importance of developing e-commerce for industrial digitalization.

To substantiate the robustness of the regression results, referring to the study of Guo et al., 2020; Du et al., 2022b, this paper replaces the core explanatory variable digitalization with the Peking University Digital Financial Inclusion Index ($DIGF$) for regression analysis.

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TABLE 1 The carbon sources and its carbon emissions coefficient.

Classification	Sources	Coefficient	Units	Reference source
Agricultural land production	Chemical fertilizer	0.896	$kg\ c/kg$	West and Marland (2002)
	Agricultural film	5.180	$kg\ c/kg$	Research Institute of Agricultural Resources and Ecological Environment of Nanjing Agricultural University
	Pesticide	4.934	$kg\ c/kg$	American Oak Ridge National Laboratory
	Diesel oil	0.593	$kg\ c/kg$	Intergovernmental Panel on Climate Change
	Plowing	312.600	$kg\ c/km^2$	College of Biology, China Agricultural University
	Agricultural irrigation	20.400	$kg\ c/km^2$	Dubey and Lal (2009)
Rice cultivation	Paddy field	4078.360	$kg\ c/km^2$	Matthews et al. (1991), Mingxing and Jing (2002)
Livestock breeding	Pigs	34.100	$kg\ c/a$	Intergovernmental Panel on Climate Change
	Cattle	418.290	$kg\ c/a$	Intergovernmental Panel on Climate Change
	Sheep	35.190	$kg\ c/a$	Intergovernmental Panel on Climate Change

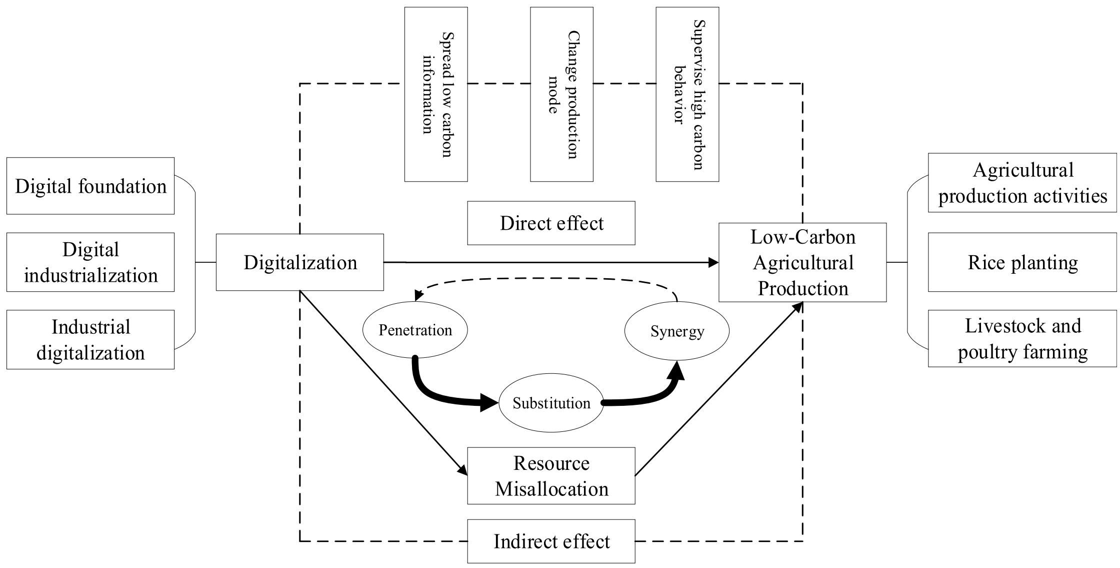

FIGURE 1
The impact mechanism of digitalization on low-carbon agricultural production.

4.2.3 Mediating variable

Agricultural capital misallocation (CMI) and agricultural labor misallocation (LMI) are mediating variables. Referring to Hsieh and Klenow (2009) and Aoki (2012), this study constructs the following theoretical framework to calculate agricultural resource misallocation.

There are i regions in the economy. Farmers in each region are price-takers in both the goods and factor markets and pay linear taxes on capital and labor inputs, which vary by region. Therefore, farmers in region i produce agricultural products given the price of the region P_i and capital and labor costs $(1+\tau_{ki})P_{ki}$ and $(1+\tau_{li})P_{li}$, respectively, where τ_{ik} and τ_{il} are the capial and labor taxes of the region, P_{ki} and P_{li} are the factor prices of capital and labor, respectively. We assume that the farmers possess the Cobb-Douglas production technology exhibiting constant-returns-to-scale (CRS). The production function can be written as follows:

$$Y_i = A_i K_i^{\alpha_{ki}} L_i^{\alpha_{li}} \tag{5}$$

Where Y_i is the output. K_i is the capital input. L_i is the labor input. A_i is the productivity of the farmer. α_{ki} and α_{li} are the output elasticity of capital and labor, calculated by the Solow residual method (Du et al., 2022a). Meanwhile, there exists $\alpha_{ki} + \alpha_{li} = 1$ under the assumption of CRS. In this setting, the profit function of the region i is written as:

$$\pi_i = P_i Y_i - (1+\tau_{ki})P_{ki}K_i - (1+\tau_{li})P_{li}L_i \tag{6}$$

Under the profit maximization objective, the first-order conditions can be described as below:

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TABLE 2 Measurement index system of digitalization.

First-level indicators	Second-level indicators	Weight	Third-level indicators	Weight
Digitalization	Digital foundation	0.407	Mobile phone switches (ten thousand)	0.037
			Mobile phone penetration (%)	0.039
			Number of domain names (ten thousand)	0.083
			Number of web pages (ten thousand)	0.170
			Long-distance cable length (km)	0.035
			Number of internet broadband interface number (ten thousand)	0.043
	Digital industrialization	0.264	Software business income (hundred million)	0.132
			Information transmission, computer services and software industry practitioners (people)	0.086
			Total telecommunications business (hundred million)	0.046
	Industrial digitalization	0.328	Number of websites owned by enterprises (unit)	0.074
			Enterprises with e-commerce activities (unit)	0.078
			Number of computers used by enterprises (ten thousand)	0.078
			E-commerce sales (hundred million)	0.098

TABLE 3 Calculation results of China's agricultural capital and labor misallocation in 2020.

Regions	Agricultural capital misallocation	Agricultural labor misallocation	Regions	Agricultural capital misallocation	Agricultural labor misallocation
Beijing	0.961	0.382	Henan	1.318	0.158
Tianjin	0.915	1.217	Hubei	0.499	0.043
Hebei	0.353	0.026	Hunan	0.244	0.056
Shanxi	0.552	0.245	Guangdong	0.566	0.114
Neimenggu	0.272	0.065	Guangxi	0.351	0.065
Liaoning	0.117	0.133	Hainan	0.545	0.354
Jilin	0.483	0.315	Chongqing	0.340	0.146
Heilongjiang	0.595	0.674	Sichuan	0.481	0.308
Shanghai	0.949	0.623	Guizhou	0.051	0.016
Jiangsu	0.830	0.469	Yunnan	0.116	0.391
Zhejiang	0.315	0.918	Shaanxi	0.015	0.113
Anhui	0.046	0.203	Gansu	0.314	0.373
Fujian	0.300	0.433	Qinghai	0.931	0.159
Jiangxi	0.315	0.013	Ningxia	0.843	0.307
Shandong	1.162	0.067	Xinjiang	0.400	0.593

$$\frac{\partial \pi_i}{\partial K_i} = P_i \frac{\partial Y_i}{\partial K_i} - (1 + \tau_{ki}) P_{ki} = 0; \quad \frac{\partial \pi_i}{\partial L_i} = P_i \frac{\partial Y_i}{\partial L_i} - (1 + \tau_{li}) P_{li} = 0 \quad (7)$$

Thus, the absolute mismatch index of capital and labor are $\gamma_{ki} = \frac{1}{1+\tau_{ki}}$ and $\gamma_{li} = \frac{1}{1+\tau_{li}}$, respectively. In practice, it is common to replace γ_{ki} and γ_{li} with γ_{ki}^{*} and γ_{li}^{*}, respectively.

$$\gamma_{ki}^{*} = \frac{K_i}{K} \Big/ \frac{S_i \alpha_{ki}}{\alpha_k}, \quad \gamma_{li}^{*} = \frac{L_i}{L} \Big/ \frac{S_i \alpha_{li}}{\alpha_l}; \quad K = \sum_i^N K_i, \quad \alpha_k = \sum_i^N s_i \alpha_{ki}, \quad L = \sum_i^N L_i, \quad \alpha_l = \sum_i^N s_i \alpha_{li} \quad (8)$$

Where γ_{ki}^{*} and γ_{li}^{*} are the relative mismatch index of capital and labor. $S_i = \frac{Y_i}{Y}$ represents the share of the agricultural output of region

i (Y_i) in the agricultural output of the whole economy (Y). $\frac{K_i}{k}$ is the proportion of capital input in the region i to the capital input of the whole economy. $\frac{S_i \alpha_{ki}}{\alpha_k}$ is the theoretical proportion of capital used by region i when capital is efficiently allocated.

In addition, to make it easy to conduct empirical tests, this paper transforms the relative mismatch index of agricultural resources as follows:

$$CMI_i = \frac{1}{\gamma^*_{ki}} - 1; \quad LMI_i = \frac{1}{\gamma^*_{li}} - 1 \tag{9}$$

$\gamma^*_{ki} > 1$ and $CMI_i < 0$ denote that the input cost of agricultural capital is low and the allocation is surplus. $\gamma^*_{ki} < 1$ and $CMI_i > 0$ indicate that the input cost of agricultural capital is high and the allocation is insufficient. Considering the negative value of agricultural resource misallocation index, this paper utilizes the absolute value of agricultural resource misallocation index in the empirical analysis. The smaller the absolute value of agricultural resource misallocation index, the lower the degree of agricultural resource mismatch. The total agricultural output, capital, and labor force are measured by the total output value of agriculture, forestry, animal husbandry and fishery, agricultural capital stock, and the number of employees in the primary industry, respectively.

Table 3 shows China's agricultural capital and labor misallocation in 2020. As seen from Table 3, there is a certain degree of mismatch between agricultural capital and labor markets in all regions of China. The agricultural capital misallocation in Henan, Shandong, Beijing, Shanghai and Tianjin is serious. Specifically, the agricultural capital misallocation index of Henan and Shandong are greater than 1, while the agricultural capital misallocation index of Beijing, Shanghai, Qinghai and Tianjin is in the range of 0.9–1.0. Compared with the agricultural capital market, agricultural labor misallocations are relatively low. Tianjin has the highest degree of agricultural labor misallocation, followed by Zhejiang, while other regions are relatively mild.

4.2.4 Control variable

Fiscal expenditure for agriculture (FAS). Fiscal expenditure for agriculture refers to the spending on agricultural production and public agricultural goods input, which can reflect government support for agricultural production. This paper uses the ratio of agricultural, forestry, and water affairs expenditure to total fiscal expenditure to measure, which is expected to have a negative impact on agricultural carbon emissions. Urbanization (URB). The proportion of the urban population and the total population is adopted to measure urbanization. Urbanization leads to the loss of the young rural labor force, and agricultural production may show aging characteristics. Constrained by cognitive level, the elderly mostly carry out extensive farming, which can lead to increased agricultural carbon emissions. Agricultural structure (STR). Grain and cash crops' carbon emissions differ substantially (Zhang et al., 2020). The ratio of grain planting area to crop planting area represents the agricultural structure, which is expected to be positively related to agricultural carbon emissions. Natural disaster (DIA) is measured by the affected area of the total sown area of crops. Generally, the higher the degree of disaster, the greater the damage to farmers' income and the ecological environment. Agricultural economic development (ADL) is an essential control variable affecting low-carbon agricultural production (Yang et al., 2022).

Considering the availability of data and the implementation of the "Broadband China" strategy, this paper uses the panel data of 30 provinces in China from 2013 to 2020 as the research sample. The data on digital inclusive finance comes from the Digital Finance Research Center of Peking University. The rest of the data is from the China Statistical Yearbook, China Rural Statistical Yearbook, China Fixed Asset Investment Statistical Yearbook, and each provincial statistical yearbook. Descriptive statistics for each variable and the correlation coefficient matrix are shown in Table 4.

5 Empirical analysis

5.1 Analysis of direct effect

5.1.1 Benchmark regression results analysis

Due to the existence of lagged explained variables in the model, merely using the OLS method may lead to biased and inconsistent estimation results (Cameron and Trivedi, 2010). Therefore, this paper employs the system GMM method, which is widely used in the dynamic panel model, to estimate the parameters. The estimation results are shown in Table 5. In the results of Table 5, columns (1) to (3) are the benchmark regression result, and columns (4) to (6) are the robustness test results with digital inclusive finance as the proxy variable for digitalization. From the estimation results of column (1), the AR (1) is less than 0.05, and AR (2) is greater than 0.1, indicating that there is no autocorrelation problem. The Hansen test cannot reject the null hypothesis that the model variable setting is over-identified at the 10% significant level, indicating that the instrumental variables selected in this paper are effective. According to the research of Bond (2002), this paper uses OLS and FE methods to estimate the dynamic panel model once more. From columns (1) to (3), the estimated coefficient of the lagged explanatory variables in the system GMM is between the FE estimation result and the OLS estimation result, which indicates that the system GMM estimation result is valid.

Specifically, in column (1), the coefficient of low-carbon agricultural production with one-period lag is significantly positive, suggesting that low-carbon agricultural production is persistent, which further proves the construction of a dynamic panel model for analysis is necessary. This finding is consistent with Pretty (2007), who argued that agriculture production sometimes accumulates carbon and thus pollutes the environment. The coefficient of digitalization is −0.089 and significant at the 1% level, suggesting that digitalization can significantly curb agricultural carbon emissions and promote low-carbon agricultural production. Hypothesis 1 is proved. The research conducted by Khan et al. (2021) using a sample of a national dataset from 7987 rural households in Afghanistan supports this conclusion, further illustrating the generality of Hypothesis 1. In the whole industrial chain of agricultural production, processing, packaging, warehousing, transportation and sales, digitalization accurately serves the decision-making behavior of production entities through intelligent perception, analysis and control systems, to reduce chemical input, energy consumption and waste of land resource, and ultimately drive low-carbon agricultural production.

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TABLE 4 Descriptive statistics and correlation matrix.

$Variables$	$lnLCA_{it}$	$lnDIG_{it}$	$lnDIGF_{it}$	$lnFAS_{it}$	$lnURB_{it}$	$lnSTR_{it}$	$lnDIA_{it}$	$lnADL_{it}$	$lnCMI_{it}$	$lnLMI_{it}$
Obs	240	240	240	240	240	240	202	240	240	240
$Mean$	5.698	2.331	5.498	2.399	4.079	4.146	5.766	9.461	1.050	0.952
$Std.Dev$	1.006	0.863	0.285	0.333	0.185	0.227	1.583	0.357	1.069	1.057
Min	2.312	0.307	4.771	1.413	3.635	3.570	0.000	8.629	−3.219	−4.605
MAX	7.168	4.353	6.068	3.015	4.495	4.575	8.349	10.461	3.062	2.697
$lnLCA_{it}$	1.000									
$lnDIG_{it}$	0.128	1.000								
$lnDIGF_{it}$	−0.150	0.499	1.000							
$lnFAS_{it}$	0.362	−0.601	−0.180	1.000						
$lnURB_{it}$	−0.515	0.562	0.532	−0.664	1.000					
$lnSTR_{it}$	0.271	0.033	−0.078	0.090	0.046	1.000				
$lnDIA_{it}$	0.722	−0.160	−0.463	0.428	−0.522	0.408	1.000			
$lnADL_{it}$	−0.259	0.734	0.770	−0.563	0.827	−0.056	−0.513	1.000		
$lnCMI_{it}$	−0.367	−0.277	0.013	0.099	0.025	−0.220	−0.317	−0.055	1.000	
$lnLMI_{it}$	−0.226	0.043	0.067	−0.096	0.238	−0.095	−0.297	0.244	0.204	1.000

TABLE 5 The results of benchmark regression.

$Variables$	$Main Regression$			$Robust Test$		
	(1) $SYS-GMM$	(2) FE	(3) OLS	(4) $SYS-GMM$	(5) FE	(6) OLS
$L.lnLCA_{it}$	1.010*** (0.011)	0.924*** (0.037)	1.011*** (0.006)	1.007*** (0.004)	0.947*** (0.035)	1.008*** (0.005)
$lnDIG_{it}$	−0.089*** (0.010)	−0.083** (0.034)	−0.014** (0.006)			
$lnDIGF_{it}$				−0.081*** (0.016)	−0.229*** (0.055)	−0.057*** (0.020)
$lnFAS_{it}$	−0.091*** (0.010)	−0.042 (0.031)	−0.002 (0.014)	0.047*** (0.009)	−0.047 (0.030)	0.028** (0.013)
$lnURB_{it}$	0.105* (0.060)	0.407** (0.169)	0.092** (0.042)	0.097*** (0.021)	0.358** (0.156)	0.084** (0.042)
$lnSTR_{it}$	−0.006 (0.026)	−0.031 (0.071)	−0.025* (0.014)	−0.014 (0.012)	0.055 (0.070)	−0.021 (0.014)
$lnDIA_{it}$	0.007*** (0.002)	0.001 (0.004)	0.005 (0.003)	0.001 (0.001)	0.001 (0.004)	0.002 (0.003)
$lnADL_{it}$	−0.041* (0.020)	−0.147** (0.059)	−0.085*** (0.021)	−0.049* (0.025)	0.073 (0.085)	−0.068*** (0.023)
$Cons$	0.294* (0.156)	0.579 (0.493)	0.457*** (0.153)	0.397*** (0.118)	−0.712 (0.617)	0.562*** (0.134)
$AR(1)$	0.001			0.001		
$AR(2)$	0.165			0.340		
$Hansen-Test$	0.568			0.454		
R^2		0.907	0.998		0.912	0.998

Note: ***,**, and * mean significance at the level of 0.01, 0.05, and 0.1, respectively; Standard errors are in parentheses.

The coefficient of fiscal spending on agriculture is negative and the association is significant, suggesting that the agricultural financial policy implemented by the government is effective. This is not surprising because Xu et al. (2022) noted that the extension of agricultural green low-carbon technology is closely related to fiscal support. However, the effect of urbanization on agricultural carbon emissions is significantly positive, implying that urbanization hinders low-carbon agricultural production. During urbanization, young laborers gradually transfer to cities, and agricultural production is characterized by aging. Bound by perceptions, older people still adopt relatively crude production methods, ultimately upturning agricultural carbon emissions. Similarly, natural disaster has a significant positive effect on agricultural carbon emissions. The reason is that before natural disasters

TABLE 6 The results of the heterogeneity test.

Variables	*Main Regression*		*Robust Test*	
	(1)	(2)	(3)	(4)
	East	*Central and West*	*East*	*Central and West*
$L.lnLCA_{it}$	0.706*** (0.205)	1.016*** (0.043)	0.900*** (0.059)	0.902*** (0.025)
$lnDIG_{it}$	−0.400* (0.210)	−0.126*** (0.016)		
$lnDIGF_{it}$			−0.340** (0.134)	−0.193*** (0.048)
$lnFAS_{it}$	0.148 (0.290)	−0.038 (0.029)	0.209 (0.193)	0.041* (0.022)
$lnURB_{it}$	−0.068 (0.611)	−0.493* (0.235)	−0.286 (0.338)	−0.252 (0.393)
$lnSTR_{it}$	−0.340 (0.703)	0.047 (0.122)	0.962* (0.451)	−0.003 (0.136)
$lnDIA_{it}$	0.014 (0.008)	0.007 (0.004)	0.005 (0.010)	0.009* (0.004)
$lnADL_{it}$	0.243* (0.110)	0.251*** (0.083)	0.390* (0.200)	0.238** (0.093)
Cons	1.715 (2.495)	−0.368 (0.620)	−4.592 (3.641)	0.279 (1.050)
$AR(1)$	0.072	0.010	0.037	0.010
$AR(2)$	0.805	0.113	0.640	0.667
Hansen – Test	0.982	0.636	0.998	0.597

Note: ***, **, and * mean significance at the level of 0.01, 0.05, and 0.1, respectively; Standard errors are in parentheses.

occur, people take preventive measures, such as covering soil film, hanging hail nets and other production activities, which all contribute to agricultural carbon emissions. The maintenance and reconstruction of agricultural infrastructure after natural disasters also intensify agricultural carbon emissions. The coefficient of agricultural economic development is significantly negative, which designates that agricultural economic growth is responsible for reducing agricultural carbon emissions, and this conclusion is supported by Sun et al. (2022). As the level of the agricultural economy rises, the constantly advancing agricultural production technology and rich agricultural production experience effectively promote low-carbon agricultural production. The planting structure variable is negative but not significant. In the results of columns (4) to (6), the coefficient of digital inclusive finance is still significantly positive, further proving the correctness and robustness of Hypothesis 1.

5.1.2 Heterogeneity analysis

Due to the obvious regional characteristics of China's economic development level and resource endowment, there are significant differences in digitalization level among provinces. This regional difference may lead to divergent effects of digitization on low-carbon agricultural production. Therefore, this paper divides the total sample into eastern, central and western regions to explore whether there is regional heterogeneity in the impact of digitalization on agricultural carbon emissions. The results are shown in Table 6.

In the results of column (1) and column (2) of Table 5, the coefficient of digitalization is significantly negative, showing that digitalization can effectively inhibit agricultural carbon emissions and give impetus to low-carbon agricultural production in both developed eastern regions and relatively backward central and western regions. However, compared with the absolute value of the digitalization coefficient, it is found that the absolute value of the digitalization coefficient in the eastern region (0.400) is greater than that in the central and western regions (0.126), the inhibitory effect of digitalization on agricultural carbon emissions in the eastern region is higher than that in the central and western regions. The finding is similar to Zhang et al. (2022), and the possible reason is that the overall level of digitalization in the central and western regions is low, and the effect of carbon emission reduction by digitalization has not yet emerged. While the level of digitalization in the eastern region is high, the agricultural emission reduction effect is obvious.

5.2 Analysis of indirect effect

Theoretical analysis shows that digitalization gives impetus to low-carbon agricultural production by reducing the misallocation of agricultural resources. To verify Hypothesis 2, this paper takes agricultural capital misallocation and agricultural labor misallocation as mediating variables and makes regression analysis step by step according to the above Eqs 1–3. The estimation results are shown in Tables 7, 8.

5.2.1 The mediating effect of agricultural capital misallocation

In Table 7, column (1) corresponds to Eq. 1. In column (1), the estimation coefficient of digitalization is significantly negative, implying that the total effect of digitalization on agricultural carbon emissions is significant. Column (2) corresponds to Equation 2. In column (2), the coefficient of digitalization is −0.946 and significant at the 1% level, suggesting that

TABLE 7 The results of the mediating effect of agricultural capital misallocation.

Variables	*Main*			*Robust*		
	(1)	(2)	(3)	(4)	(5)	(6)
$L.lnLCA_{it}$	1.010*** (0.011)	0.159*** (0.008)	1.004*** (0.007)	1.007*** (0.004)	0.206*** (0.018)	1.015*** (0.007)
$lnDIG_{it}$	−0.089*** (0.010)	−0.946*** (0.050)	−0.041*** (0.011)			
$lnDIGF_{it}$				−0.081*** (0.016)	−0.371*** (0.125)	−0.080*** (0.021)
$lnCMI_{it}$			0.010** (0.004)			0.018*** (0.004)
$lnFAS_{it}$	−0.091*** (0.010)	−0.548*** (0.152)	−0.039** (0.017)	0.047*** (0.009)	0.579*** (0.121)	0.034** (0.012)
$lnURB_{it}$	0.105* (0.060)	−0.049 (0.574)	0.060 (0.049)	0.097*** (0.021)	1.267* (0.621)	0.126** (0.060)
$lnSTR_{it}$	−0.006 (0.026)	−0.665*** (0.170)	−0.049* (0.026)	−0.014 (0.012)	−0.699*** (0.248)	−0.035 (0.039)
$lnDIA_{it}$	0.007*** (0.002)	−0.036*** (0.007)	0.011*** (0.002)	0.001 (0.001)	−0.136*** (0.025)	0.004* (0.002)
$lnADL_{it}$	−0.041* (0.020)	1.230*** (0.199)	−0.050* (0.027)	−0.049* (0.025)	−0.247 (0.303)	−0.055 (0.033)
Cons	0.294* (0.156)	−3.982** (1.636)	0.506*** (0.148)	0.397*** (0.118)	2.394* (1.398)	0.365* (0.189)
$AR(1)$	0.001	0.028	0.001	0.001	0.004	0.001
$AR(2)$	0.165	0.172	0.319	0.340	0.165	0.434
$Hansen-Test$	0.568	0.751	0.462	0.454	0.779	0.432

Note: ***, **, and * mean significance at the level of 0.01, 0.05, and 0.1, respectively; Standard errors are in parentheses.

TABLE 8 The results of the mediating effect of agricultural labor misallocation.

Variables	*Main*			*Robust*		
	(1)	(2)	(3)	(4)	(5)	(6)
$L.lnLCA_{it}$	1.010*** (0.011)	0.148*** (0.022)	1.024*** (0.011)	1.007*** (0.004)	0.795*** (0.029)	0.954*** (0.014)
$lnDIG_{it}$	−0.089*** (0.010)	−1.701*** (0.253)	−0.058*** (0.010)			
$lnDIGF_{it}$				−0.081*** (0.016)	−0.535*** (0.154)	−0.071** (0.027)
$lnLMI_{it}$			0.012*** (0.004)			0.008* (0.004)
$lnFAS_{it}$	−0.091*** (0.010)	−1.715*** (0.252)	−0.089*** (0.013)	0.047*** (0.009)	0.124 (0.126)	0.136*** (0.014)
$lnURB_{it}$	0.105* (0.060)	−0.649 (0.918)	−0.002 (0.065)	0.097*** (0.021)	−1.334*** (0.401)	0.042 (0.112)
$lnSTR_{it}$	−0.006 (0.026)	−0.990** (0.419)	−0.135** (0.053)	−0.014 (0.012)	0.279 (0.235)	0.104* (0.054)
$lnDIA_{it}$	0.007*** (0.002)	0.092*** (0.030)	0.015*** (0.003)	0.001 (0.001)	−0.095*** (0.013)	0.006* (0.003)
$lnADL_{it}$	−0.041* (0.020)	2.843*** (0.511)	0.012 (0.027)	−0.049* (0.025)	0.990*** (0.352)	−0.045 (0.055)
Cons	0.294* (0.156)	−11.807*** (4.235)	0.557** (0.217)	0.397*** (0.118)	−1.681 (1.529)	0.086 (0.199)
$AR(1)$	0.001	0.006	0.001	0.001	0.006	0.002
$AR(2)$	0.165	0.708	0.316	0.340	0.563	0.634
$Hansen-Test$	0.568	0.577	0.481	0.454	0.913	0.533

Note: ***,**, and * mean significance at the level of 0.01, 0.05, and 0.1, respectively; Standard errors are in parentheses.

digitalization can effectively relieve agricultural capital misallocation. Column (3) corresponds to Eq. 3. Both digitalization and agricultural capital misallocation pass the significance test, suggesting that agricultural capital misallocation plays an intermediary role between digitalization and agricultural carbon emissions. Combined with the estimation results of column (1), after adding the mediating variable, the absolute value of the coefficient of digitalization has decreased, implying that agricultural capital misallocation plays a partial mediating role. Digitalization alleviates the information asymmetry in the farmers' financing process and enhances financial institutions' motivation to supply funds. Financial institutions provide farmers with agricultural machinery loan subsidies, technical subsidies, and agricultural insurance through innovative financial products, thereby mitigating the degree of agricultural capital misallocation, decreasing agricultural carbon emissions, and ultimately driving low-carbon agricultural production. In this paper, digital inclusive finance is used as a proxy variable of digitalization for regression estimation again, and the results remain unchanged.

5.2.2 The mediating effect of agricultural labor misallocation

In Table 8, columns (1) to (3) correspond to Eqs 1–3. The results and meanings of column (1) are the same as those reported in column (1) of Table 7. Column (2) reports the impact of digitalization on agricultural labor misallocation. The estimation coefficient of digitalization is significantly negative at the 1% level, illustrating that digitalization optimizes agricultural labor allocation and significantly reduces the degree of misallocation, which is in line with expectations. Column (3) reports the estimation results after adding digitalization and agricultural labor misallocation. Among them, the coefficient of digitalization is negative, and the coefficient of agricultural labor misallocation is positive, but both pass the significance test. This implies that digitalization can curb agricultural carbon emissions by relieving the agricultural labor force misallocation. By calculating the estimation coefficient, the ratio of the mediating effect and the total effect of agricultural labor misallocation is 0.229. In other words, 22.9% of the inhibitory effect of digitalization on agricultural carbon emissions is achieved by optimizing agricultural labor allocation. This manifests that agricultural labor misallocation plays an important role in low-carbon agricultural production. After re-estimating digital inclusive finance as a proxy variable for digitalization, it is found that agricultural labor misallocation still plays a partial mediating effect between digitalization and agricultural carbon emissions. This further proves the robustness of the estimation results.

6 Conclusion and implications

This paper contributes new evidence to discuss the relationship between digitalization and low-carbon agricultural production, which provides new ideas for agricultural production to jump out of the dilemma of high input and high energy in China. The results indicate that digitalization inhibits agricultural carbon emissions, and this suppression effect is more obvious in eastern China. In addition, by optimizing agricultural resource allocation, digitalization can reduce the degree of agricultural capital and labor misallocation, thus positively impacting low-carbon agricultural production. Based on the findings of this paper, the following policy implications can be drawn.

First, the government may carry out top-level design and planning for the digital transformation of traditional agriculture to regulate the investment and construction of digital infrastructure in agriculture and rural areas. It should take local conditions into full consideration and carry out digital infrastructure in a gradual and orderly manner to improve the efficiency of resource allocation.

Second, in addition to promoting the construction of digital agricultural infrastructure, the government also focuses on improving farmers' agricultural production skills and digital literacy. For example, the government may cooperate with agricultural technology promotion departments, cooperatives and leading enterprises to build a skills learning platform for farmers to enhance their ability to apply digital agricultural machinery and improve their understanding of sustainable production.

Third, the government may accelerate the allocation of public resources to agriculture and rural areas, and get over the mechanism and institutional shortcomings, so that the market can play a leading role in allocating urban and rural factors and public resources. Meanwhile, the government can refine relevant laws and regulations, strengthen the flow mechanism of agricultural production factors, reduce barriers to the entry of capital, labor, and other agricultural production factors into agricultural operations, and give full play to the optimal effect of digitalization on agricultural resource allocation.

This paper provides a preliminary discussion of the relationship between digitalization, resource misallocation and low-carbon agricultural production but much remains to be done. First, this paper merely analyzes the impact of digitalization on low-carbon agricultural production from a macro perspective. Future studies may expand the perspective to the micro level on the condition that farmers' level data can be obtained. Second, this paper primarily concentrates on the mediating effect of agricultural capital and labor misallocation in the relationship between digitalization and low-carbon agricultural production. However, agricultural production also involves natural resources such as land and water. In the future, it is necessary to calculate the level of land misallocation further and verify its environmental effects. Third, this study only focuses on China and the conclusions may not be suitable for other countries. Future studies could be further extended to other countries or even to the global level.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

Conceptualization, YX; methodology, YX; formal analysis, YX; writing—original draft preparation, YX and JW; writing–review and editing, XW; supervision, CL. All authors have read and agreed to the published version of the manuscript.

Funding

This work was funded by the National Natural Science Foundation of China (The effect of infant milk powder safety trust index on product competitiveness—Index measurement, Correlation model construction and market simulation, No. 71673042) and the Propaganda Department of the Central culture and "four batch" talent self-selected project, "Comparative Study on the Competitiveness of Chinese Dairy Products" (No. 201801).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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